Investor overconfidence under the adaptive markets hypothesis in selected African stock markets

Jameson Nyasha

218028168

UNIVERSITY OF KWAZULU-NATAL ™

INYUVESI YAKWAZULU-NATALI

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Supervisor:	**Prof. Paul-Francois Muzindutsi**
Co-Supervisor:	**Dr. Odunayo Magret Olarewaju**
Co-Supervisor:	**Dr. Lorraine Muguto**

DECLARATION

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DEDICATION

This thesis is dedicated to my parents and siblings, who supported and encouraged me to complete this program despite the many challenges I faced during this time.

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One inspired mind and the world will never be the same. Inspired people inspire people. You can never start a fire with wet matches. Isaac Newton, the great scientist, once said: *"If I can see further than others, it is because I have stood on the shoulders of giants."*

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ABSTRACT

Meticulous empirical research remains to determine whether the Adaptive Markets Hypothesis (AMH) or the more widely known Efficient Market Hypothesis (EMH) better explains investor overconfidence and stock return volatility behaviour. Investor overconfidence is vital in understanding why investment strategies are pursued so aggressively, leading to excessive market trading. It is often argued that the investor overconfidence bias makes markets less efficient because it creates pricing errors in extreme volatility and overestimates investors' beliefs in the accuracy of their forecasts of their quotes on prices. This research analyses the effect of investor overconfidence on the volatility of stock market returns according to the AMH in seven African stock markets, including the Casablanca Stock Exchange, the Egyptian Exchange, the Johannesburg Stock Exchange, the Nigerian Stock Exchange, the Nairobi Stock Exchange, the Ghana Stock Exchange, and the Stock Exchange of Mauritius. The sample period includes secondary time series data from January 2005 to December 2019. The first goal was to develop and validate a measure of investor overconfidence. The second objective was to compare different levels of investor overconfidence in the selected African stock markets. The third objective was to evaluate the influence of investor overconfidence on the volatility of stock market return under changing market conditions, as described by the AMH.

The estimation methods included the Generalised Methods of Moments dummy regression, regime-switching VAR models and rolling GARCH models, which are GARCH, EGARCH and TARCH. The results show that high investor overconfidence is more associated with bullish markets than periods of financial crises and bearish markets. The results also imply that it is not advisable to generalise the impact of market conditions on investor overconfidence across all the markets. Additionally, rolling GARCH estimates demonstrated that patterns of investor overconfidence evolve, consistent with the AMH. Assessing investor overconfidence under the AMH framework offers a stronger image of the adaptive behaviour of the African equity markets. This research adds to existing knowledge in numerous ways. Foremost, it provides a standard measure of investor overconfidence in Africa's equity markets. A measure that combines multiple proxies into a single index and neutralizes the disadvantages of each proxy when used separately to estimate investor overconfidence. Second, it provides a timely contribution to the effect of investor overconfidence on stock return volatility in African equity markets under the AMH paradigm. Third, according to the AMH, investor confidence is not

static and can appear under specific market conditions and disappear under others. This bias occurs and disappears as market conditions change in the chosen African equity exchanges. This also shows that investor overconfidence is normal, changes over time and is adaptable in the African stock markets. Consequently, this study brings a new perspective regarding investor overconfidence and market efficiency in the face of the AMH paradigm. The results also have important implications for investors and brokers wishing to develop appropriate trading strategies. This study is also helpful for policymakers as they need to be wary about investor overconfidence impact on market momentum in periods of market expansion. This study argues that investor overconfidence in African stock markets conforms to the AMH than the EMH and the BF.

Keywords: Investor overconfidence, stock return volatility, Adaptive markets hypothesis.

LIST OF COMMON ACRONYMS

ADF	Augmented Dickey-Fuller
ADF	Dickey and Fuller
AIC	Akaike Information Criterion
ALTX	East Africa Exchange
AMEX	American Stock Exchange
AMH	Adaptive Markets Hypothesis
AR	Autoregressive
ARCH	Autoregressive Conditional Heteroscedasticity
ARMA	Autoregressive Moving Average
ARRT	Average Market-Adjusted Returns
ASEA	African Securities Exchange Association
AU	African Union
ATLF	Africa Tax, Law, Finance Hub
BF	Behavioural Finance
BSE	Bombay Stock Exchange
CAPM	Capital Asset Pricing Model
CAR	Cumulative Adjusted Returns
CFA	Certified Financial Analyst
CRSP	Centre for Research in Security Prices
CSE	Casablanca Stock Exchange
DGP	Data Generating Process
EGARCH	Exponential Generalised Autoregressive Conditional Heteroscedasticity
EGX	The Egyptian Exchange
EGX30	Egypt Exchange Benchmark Index,
EMH	Efficient Market Hypothesis
ERS	Elliot, Rothenberg, and Stock
FTSE	Financial Times Stock Exchange
GARCH	Generalised Autoregressive Conditional Heteroscedasticity
GED	Generalized Error Distribution
GMM	Generalised Methods of Moments
GSE	Ghana Stock Exchange

GSE-CI	Ghana Stock Exchange Composite Index
IMF	International Monetary Fund
IRF	Impulse Response Function
JALSH	Johannesburg Stock Exchange All Share Index
JB	Jarque-Bera
JSE	Johannesburg Stock Exchange
K	Kurtosis
KPSS	Kwiatkowski, Phillips, Schmidt, and Shin
LB	Ljung-Box
LM	Lagrange multiplier
LS	Lee and Strazicich
MA	Moving Average
MAD	Mean Absolute Deviation
MANOVA	Multivariate Analysis of Variance
MCAP	Market Capitalisation
MOSENEW	Morocco/Casablanca MASI Free Float All Share Index
MS-VAR	Markov Switching Time Series Vector Autoregressive
M & A	Mergers and Acquisitions
NGX	Nigeria Stock Exchange
NGXINDX	Nigeria Stock Exchange All Share index
NP	Ng and Perron
NSE	Nairobi Stock Exchange
NSEASI	Nairobi Stock Exchange All Share Index
NYSE	New York Stock Exchange
OLS	Ordinary least squares
OR	Order Ratio
PhD	Doctor of Philosophy
PP	Phillips-Perron
REIT	Real Estate Investment Trust
S	Skewness
SA	South Africa
SAEF	School of Accounting, Economics and Finance
SBIC	Schwartz Bayesian Criterion
SEM	Stock Exchange of Mauritius

SEMDEX	Stock Exchange of Mauritius All Share Index
SUR	Seemingly Unrelated Regression
TARCH	Threshold Generalised Autoregressive Conditional Heteroscedasticity
TB	Location of the structural break (TB)
TOM	Turn of the Month
UK	United Kingdom
UKZN	University of KwaZulu Natal
UN	United Nations
US	United States
USA	United States of America
USE	Ugandan Securities Exchange
VaR	Value-at-Risk
VAR	Vector Auto Regression
VECM	Vector Error Correction Model
VFEX	Victoria Falls Exchange

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CHAPTER 1: THE INTRODUCTION AND BACKGROUND TO THE STUDY

1.1 Background to the Study

Early financial theories, such as Fama's (1970) Efficient Market Hypothesis (EMH), were developed centred on the supposition of rational investors. They make logical/sound decisions (Titan, 2015) and view the market as frictionless. The investor rationality hypothesis assumes that investors are utility-maximizing entities, making investment decisions based on risk-return trade-offs (Kumar & Prince, 2022). Elbanna (2006) define rationality as reasons behind actions and judging behaviour as rational, which can be understood within a specific frame of reference. Rationality characterises rational behaviour in tracking aims (Trejos, 2017). Nevertheless, rationality has been extensively criticised due to lack of validation and empirical tests (Buskens, 2015). Instead of relying on subjectivity and intuition, sound decision-making uses objective data, logic, and analysis to help solve problems and achieve goals. It is a methodical approach that allows you to recognise a problem, choose a course of action from various options, and provide feedback (Chii, 2018). Poyry (2014) defines a frictionless market as a business environment without transaction costs, taxes, fees, or other transaction barriers. Friction is a type of market imperfection.

Fama (1970) argued that in an efficient market, at any given time, the actual price of a financial product will be an accurate estimate of its intrinsic value. The efficient market hypothesis is based on three main assumptions:

- i) rational investors,
- ii) in the case of some irrational investors, their trades are random and cancel each other without affecting the price and
- iii) rational arbitrageur's price deviations will eliminate the influence of irrational investors in the market.

There is an old joke often told by economists to illustrate the assumptions of the EMH. "*Imagine, one afternoon, you are walking to the mall with your economist friend, and then you see a $100 bill lying on the street. You stop to pick it up. Your friend then stops you by claiming the bill would have been picked if it were a real $100 bill"* (Lo, 2004, p. 2). This humorous illustration of economic reasoning gone askew is, in some ways, a perfect explanation of the EMH. EMH, also known as efficient market theory, is a hypothesis that share prices represent every available information and that it is challenging to generate constant alpha. Under the market efficiency assumption, prices completely reflect every available relevant information, public, private or both, and reflect the intrinsic value of assets at all times (Fama, 1970). According to EMH, shares will still trade on exchanges at fair value, rendering it harder to buy undervalued shares or sell overvalued shares. Therefore, through expert stock selection or market timing, it will not be easy to consistently outperform the overall market (Fama, 1970). Consequently, using public and historical information to predict potential price changes is impossible, making technical and fundamental analysis irrelevant. EMH has attracted many research works (Lo & MacKinley, 1999; Sewell, 2012; Konak & Seker, 2014; Titan, 2015; Lobão, 2018; Kelikume, Olaniyi, & Iyohab, 2020), both experimental and analytical. EMH is famous and influential in the modern financial path in theory and practice. However, this is one of the most intensely contested proposals of the neoclassical school of finance.

The concept of efficient markets was born by Bachelier (1900) in the early 20th century in his doctoral thesis in mathematics at the Sorbonne. He discovered that stock prices necessarily fluctuate randomly. Samuelson (1965) attempted to explain why stock prices fluctuate randomly, but Fama (1965) formalised the EMH by coining the term “efficient market” to finance. The concept of an efficient market was explained by Fama (1970) as a market of many rational investors seeking to maximise their profits, actively challenging one another, trying to forecast the future market values of the assets and all related assets and important information is available at any time at no costs for all market participants. This market is where asset prices immediately reflect all new information (Bodie, Kane & Marcus, 2023). One of the building blocks of the EMH is that no investor can be more intelligent than the market at any time because investors always have the same information (Fama, 1970). Investing in financial assets requires mastery and understanding of the stock market, and instead of getting regular returns, some investors want to achieve better results than the stock market (Shah, Raza & Khurshid, 2012). Making sound decisions is an important skill, especially in the investment industry. Chii (2018) argues that because investors are emotional people, their biases and beliefs can distort their worldview. Luckily, data helps them see things clearly. This frees them from the obligation to make assumptions about market behaviour.

Over the years, EMH has dominated financial thinking, but Behavioural Finance (BF) has evolved to challenge EMH. Sewell (2010) defines behavioural finance as studying psychology’s influence on investors’ behaviour and succeeding effects on markets. It is interesting since it aids explain how and why markets can become inefficient. Toma (2015) posits that behavioural finance is a field that captures investor irrationality, the biases that investors are susceptible to. Behavioural finance refers to philosophies and tests focusing on what transpires when investors make judgements influenced by or in conjunction with emotions (Trejos, 2017). These cognitive errors are because investors cannot know with certainty what the market will do in the next periods, which encourages them to make biased decisions (Toma, 2015). However, these can be both harmful and beneficial to their wealth.

Since the seminal work of Tversky and Kahneman (1974), these two schools of thought have gained acceptance. Traditional theories based on EMH and behavioural theory consider the impact of social, cognitive, and emotional factors on financial decision-making (Ganesan, 2013). The observation of market anomalies have led to introduction of behavioural and psychological factors into economic and financial fields and formation of the behavioural finance school of thought (Çömlekçi & Özer, 2018). BF studies the psychological aspects of financial practitioners' behaviour and its influence on financial decisions and the stock market (Sewell, 2010). BF began in the era of Vilfredo Pareto, Adam Smith and John Maynard Keynes, but current developments are attributed to work by De Bondt and Thaler (1985). They studied whether stock market overreacted, found that people seemed to overreact to bad news, causing the stock market to become inefficient. Their findings imply that markets are inefficient and that investor behaviour affects efficiency. Metwally and Darwish (2015) point out that many previous psychological experiments in finance concluded that investors are not always rational and have systematic cognitive biases that causes deviation from the conclusions reached by classical finance. Awale, Pandey, Sapkota, and Shrestha (2018) argue that although most investors believe themselves to be rational, behavioural finance theories suggest that investors have emotional biases that cause them to express biases in information processing and other biases, such as investor overconfidence.

Investors don't always make significant decisions. They do not always consider the risk-return trade-off before investing. Sometimes, they invest by seizing opportunities or following their investment experts, and sometimes in proximate companies' stocks (Kumar & Prince, 2022). Their rational reasoning comes not only from passion and emotion but also from internal biases about their own abilities. Their investment decisions are often guided by their emotions, experience, and instincts (Tversky & Kahneman, 1974). BF calls these feelings heuristics, instincts, and behavioural biases. Overconfidence is one of the common biases in financial markets. This overconfidence bias is a powerfully established trait of individual behaviour in psychological research and has been significantly suggested to explain inefficient market outcomes (Proeger & Meud, 2014). In Daniel and Hirshleifer (2015) and Moore, Tenney, and Haran (2014), overconfidence is considered the mother of all other biases in the stock market because it creates the conditions for other biases to arise. Investor overconfidence is said to be a significant bias in African stock markets such as the Egyptian Stock Market (Metwally & Darwish, 2015) Nigerian stock market (Aigbovo & Ilaboya, 2019) and the Nairobi Stock Exchange (Werah, 2006; Mwaka, 2013).

Odean (1998) describes overconfidence as an individual's inclination to overrate the accuracy of their asset valuation know-how. It is often defined as overestimating knowledge or accuracy of individual information and underestimating signal bias or asset price volatility (Metwally & Darwish, 2015). Shiller (2000) describes overconfidence as overtrading, implying that overconfident investors tend to open too many trading positions. Investor overconfidence can be divided into over + confidence. More than apt confidence is overconfidence (Kumar & Prince, 2022). Excessive confidence in one's own knowledge, accuracy, abilities, and luck causes investors to be overconfident (Lichtenstein et al., 1977). This is not to say that overconfidence is the universal explanation for all market anomalies, but it is a fundamental factor in evaluating financial decisions. The investor overconfidence hypothesis has successfully explained several problems in financial markets that previously defied classical economic theory. These market conundrums primarily revolve around persistent undervaluation of securities, the emergence of overtrading (Daniel, Hirshleifer, & Subrahmanyam, 1998; De Bondt & Thaler, 1985), the disposition effect discovered by the works of Kahneman and Tversky (1979), excessively borrowing (Barros & Da Silveira, 2007; Sullivan, 2009) and stock price volatility (Benos, 1998; Odean, 1998).

Several studies have shown that financial markets often have anomalies, such as short-term momentum and high trading volumes (Statman, Thorley & Vorkink, 2006; Metwally & Darwish, 2015; My, Toan & Cuong, 2016). Over the past decades, several events (such as bubbles and financial crises) have shown that market efficiency is not static. Several currency and commodity crises have characterised recent decades. These events included the foreign exchange crisis of 1992–1993, the Mexican peso financial market crisis of 1994, and the 1997 and 1998 financial crises in Asia and Russia, respectively. The Brazilian currency crisis of 1999, the Internet bubble burst in 2000, and the 2007-2009 global financial crisis (Tariq and

Ullah, 2013), the Greek sovereign debt crisis in 2010, whose consequences are still present, and the Argentine stock market crash of 2019. (Bloomberg, 2019). More recently, the COVID-19 pandemic has significantly impacted investor sentiment and confidence (Kumar & Prince, 2022), and the war between Russia and Ukraine broke out in 2022. Some of these events indicate that markets are sometimes inefficient, while investor reactions to some tend to demonstrate irrational investor behaviour. For example, Kedar-Levy (2020) shows that a market crash means the price discovery process does not reach equilibrium. This reflects market inefficiencies, implying that fundamental changes alone cannot explain these events (Yeh and Yang, 2011).

EMH does not provide solutions to these and other conundrums that arise in financial markets. On the other hand, behavioural aspects such as investor overconfidence and other biases described by behavioural finance theory have been blamed as the leading cause of all market crises. A number of academics proposed models based on the investor overconfidence hypothesis to explain these anomalies (for example, Benos, 1998; Odean, 1998; Gervais & Odean, 2001). However, obtaining a reliable measure of investor overconfidence has proven to be a key issue in scientific research (Merkle & Weber, 2011; Michailova & Katter, 2014; Olsson, 2014; Parker & Stone, 2014; Spiwoks & Bizer, 2018). No clear and perfect method for measuring investor overconfidence has been developed (Deaves, Luders & Luo, 2008). Consequently, Spiwoks and Bizer (2018) warn against being too confident in measuring overconfidence, as this can lead to a biased analysis. Challenges in measuring overconfidence are also expected in African stock markets that are considered illiquid. Therefore, this study intends to extend this debate further by developing and proposing a standard metric for African stock markets.

In light of the growing body of evidence against the EMH, Campbell, Lo, and MacKinlay (1997) proposed a relative efficiency idea. This has steered researchers' move from examining total market efficiency to assessing the level of market efficiency. Having observed that humans are neither wholly rational nor completely irrational, this implies that neither rationalists nor behaviourists are completely convincing. A new theory, the Adaptive Markets Hypothesis (AMH) of Lo (2004), which lies between EMH and BF, has been proposed. This hypothesis is based on the evolutionary principles of behavioural economics, specifically natural selection, reproduction, competition, and mutation. In this theory, EMH can coexist with BF intellectually constantly (Lo, 2005). Lo (2005) argues that many examples given by behaviourists of rationality violations that contradict the market efficiency hypothesis (e.g., overconfidence plus additional behavioural biases) conform to the evolutionary model of organisms adapting to environmental changes through simple heuristics. In this hypothesis, market efficiency is a principle that constantly changes depending on market conditions and times (Mobarek & Fiorante, 2014). Lim and Brooks (2011) also support the idea that efficiency changes over time. From an AMH perspective, this implies that investor confidence is not static and would appear under specific market conditions and disappear under others. Several researchers (Urquhart & Hudson, 2013; Urquhart & McGroarty, 2016; Almail & Almudhaf, 2017; Obalade & Muzindutsi, 2018; 2019; 2020a) have examined the validity of the AMH, but to date, the investor overconfidence bias have not been studied through the notion of AMH concept, especially in the context of African equity markets considered illiquid and inefficient (Ntim, 2012).

Overconfident investors place too much emphasis on the accuracy of their ability to value, meaning they overestimate the precision of their personal data metrics (Daniel, Hirshleifer & Subrahmanyam, 2004; Gervais & Odean, 2001). In global financial markets, high trading volumes have been observed and are considered a result of investor overconfidence. Overconfident investors are expected to engage in more aggressive trading than rational investors. This is a detriment to their wealth than just adopting a conservative buy-and-hold strategy (Reuvers, 2018). Investors' passion for active trading in the stock market is widespread. Despite data showing that trading frequency and stock returns are negatively correlated, people trade speculatively when the market enters a bullish phase (Odean, 1999; Magron, 2014). Even in times of changing market conditions, due to overconfidence bias, it is still tempting to try to time the market, that is, choose entry and/or exit points (Reuvers, 2018). It remains to be seen whether investor overconfidence changes depending on market conditions.

Overconfident investors turn to under-diversification, convinced that their forecasts are correct, and there is no need to hedge. Hirshleifer and Luo (2001) posit that overconfident investors exist in competitive exchanges mainly because they are willing to take on more risk, hoping to benefit from valuation errors resulting from the actions of noise and liquidity traders. Hence, there is a tendency to trade in risky assets. If a market has many overconfident investors, market price volatility tends to increase due to their frequent and speculative trading (Odean, 2007). Shiller (1981), among other authors, posits that the EMH does not explain high volatility in asset prices, although investor overconfidence is said to cause excessive volatility. Studies by Daniel, Hirshleifer and Subrahmanyam (1998), Odean (1998), Gervais and Odean (2001), Scheinkman and Xiong (2003) and Chuang and Lee (2006) show that there is a positive relationship between investor overconfidence and volatility. Investor overconfidence can be more easily seen and stronger in bull markets than in other market periods, such as normal or bear markets (Daniel, Hirshleifer & Subrahmanyam, 2001; Gervais & Odean, 2001). The latter's model predicts that investor overconfidence and its side effects, excessive trading and excessive volatility tend to increase at the end or immediately after a bull period. Therefore, the positive relationship between present trading volume and past returns is expected to be deeper at end or immediately after bullish periods than in other market periods (Chuang & Lee, 2006). This raises the question of whether such a statement holds true for all markets, especially illiquid markets like Africa.

Although overconfidence often costs investors dearly and causes many problems in the market, it can generally bring profits and gains (Johnson & Fowler, 2011; Daniel & Hirshleifer, 2015). This may cause investors to scrutinise and trade more based on their signals, leading to better information incorporation into prices (Hirshleifer, Subrahmanyam & Titman, 1994; Hirshleifer & Lou, 2001; Daniel & Hirshleifer, 2015). This overconfident behaviour of investors can lead to more efficient markets and equilibrium (Shah, Raza & Khurshid, 2012). Overconfidence can heighten desire, motivation, persistence, or sincerity of bluffing and lead to a self-fulfilling prediction in which overconfidence increases the chances of winning (Johnson & Fowler, 2011). This encourages investors to get involved in other asset classes and even try their hand at international investing (Daniel & Hirshleifer, 2015). Therefore, evaluating investors' overconfidence in the new AMH theory, which talks about market efficiency changing over time, is important.

The International Monetary Fund (IMF) (2016) highlights that African markets have grown and improved significantly as various countries have undertaken economic and political reforms, experienced fewer violent wars, and moved towards new democracy. Positive stock returns attract international investors seeking diversification benefits for their portfolios (Almudhaf, 2016). In recent years, corporate listing figures on the Nigerian Stock Market have increased significantly as investors have rushed to buy shares, demonstrating repeated oversubscription (Aigbovo & Ilaboya, 2019). However, many investors face losses due to overconfidence, as evidenced by Transcorp's initial public offering (Aigbovo & Ilaboya, 2019). In a study by Almudhaf (2016), bubbles were documented in emerging and frontier African stock markets, specifically Tunisia, Botswana, Nairobi, Nigeria, Egypt and Ghana. He notes periods of explosive behaviour in the dividend-price relationship that indicate irrational exuberance.

Developing markets are considered more susceptible to bubbles than developed markets, making investors nervous. Shiller (2005) argues that these bubbles may result from behavioural factors stemming from irrational behaviour, such as herd behaviour and investor overconfidence. Dessí and Zhao (2017) argue that overconfidence varies significantly across countries. The key factor in the difference in overconfidence is the degree of environmental stability. Too many changes lead to excessive overconfidence beliefs (Dessí & Zhao, 2017). The internet has transformed the distribution and use of information among investors (Barber & Odean, 2001) by allowing investors to exchange information directly, bypassing stock brokers. This can cause investors to feel more and more influence over trading outcomes. Additionally, with access to large amounts of online data, investors are increasingly overconfident in their capacity to choose stocks, and their choices can affect stock prices. This innovative technology could increase the link between investor overconfidence and stock return volatility. This, therefore, calls for further research into the auspicious scholarship of Africa.

The ongoing debate over the robust notion of efficient markets and the rationality of economic agents has been sparked with the possibility of investor overconfidence in exchanges and its persistence over time. The prevalence of investor overconfidence in financial markets has been routinely demonstrated using techniques such as formal models, financial market data, questionnaires and experimental studies, despite considerable scepticism among economists about its existence and impact. Several studies in the African market (Katusiime, Shamsuddin & Agbola, 2015; Njuguna, 2016; Obalade, 2019; Obalade & Muzindutsi, 2020a, 2020b) have presented evidence of the AMH, suggesting that investor overconfidence bias and other related biases in African equity markets may be adaptive, contradicting the widespread view that African markets are inefficient and illiquid. The present study, therefore, aims to close this gap through applying different tests of investor overconfidence in selected African stock markets in the context of AMH of Lo (2004).

1.2 Statement of the Problem

Investor overconfidence is considered the most powerful and pervasive bias affecting human judgment (De Bondt & Thaler, 1995; Kahneman, 2011). Understanding overconfidence tells us what happens to the wealth and portfolios of overconfident investors. Are they often rewarded? Do they always suffer losses on their investments? The main concern is determining the presence of investor overconfidence, as no clear technique is available to quantify investor overconfidence (Michailova & Katter, 2014; Langnickel & Zeisberger, 2016; Spiwoks & Bizer, 2018). Previous studies have often used questionnaires to extrapolate results to measure overconfidence. Finding a suitable measure or index of investor overconfidence remains challenging because only a few studies (Ho, 2011; Tekce & Yilmaz, 2015) have investigated more than one way to measure investor overconfidence. This calls for the need to develop and validate a common measure of investor overconfidence in African equity markets, as preceding measures have mostly concentrated on the developed markets of Europe or the United States (US), which have different characteristics from those markets of Africa.

One of the unexplained features currently found in African stock markets, for example the Johannesburg Stock Exchange (South Africa National Treasury, 2018) and the Nigerian Stock Exchange (Aigbovo & Ilaboya, 2019), is a sharp increase in trading volume. The technology boom has changed the shape and scope of African stock markets. The Internet has helped investors access information quickly, which can increase their sense of control over investment outcomes, thereby making them more confident in their own abilities. Investors from different parts of the world now have access (Almudhaf, 2016), and their growing demand for African markets could lead to overconfidence in African markets, previously considered illiquid and largely inefficient (Ntim, 2012). A study by Metwally and Darwish (2015) observed that there is high (low) trading activity after market gains (losses), especially during bull (bear) markets of the Egyptian market. Aggressive trading by overconfident investors contributes to excessive stock return volatility (Metwally & Darwish, 2015). However, the big question is whether this bias would change as market conditions change. African markets, like other emerging markets, have market efficiency issues. The market operates fairly and operates with good integrity. However, they lack liquidity, price providers and depth (South Africa National Treasury, 2018), are at risk of speculative behaviour and are considered inefficient (Ntim, 2012; Vitali & Mollah, 2010). However, African markets have proven to be adaptive (Obalade & Muzindutsi, 2018; 2019; 2020a), and AMH's presence in African markets may indicate that investors overconfident in the African markets may be subject to changing conditions and must therefore be investigated. AMH provides an ideal opportunity to assess market efficiency and investor overconfidence in Africa's small and underdeveloped markets.

As in previous studies, analysing investor overconfidence in absolute terms can be misleading. This requires a new way to investigate investor overconfidence under the AMH, which supports time-varying market efficiency and changing market conditions. Therefore, this understanding means that if the market is efficient, investors do not tend to be overconfident and vice versa. AMH claims that efficiency changes over time; does this imply that investor overconfidence also changes over time? Is the degree of investor overconfidence also varying? If AMH claims that efficiency is affected by changes in market conditions, does this mean that investor overconfidence is affected by changes in market conditions? So, how does the change in investor overconfidence affect the volatility of stock returns in response to these changing market conditions? These critical questions need empirical investigation, especially in the context of emerging African markets.

1.3 Research Objectives

The central goal of this study was to test for investor overconfidence within the AMH paradigm in selected African Stock Markets. The explicit objectives of this study are, thus, to:

i. Develop and validate a measurement for investor overconfidence in selected African Stock markets;
ii. Compare the varying degrees of investor overconfidence in the selected African Stock markets and,
iii. Assess the effect of investor overconfidence on stock return volatility under changing market conditions as portrayed by the AMH.

1.4 Research Questions

In light of achieving the above-set goals, it is vital that this study provides solutions to the subsequent questions:

i. What is the conventional measure for investor overconfidence in the selected African Stock Markets context?
ii. How does the degree of investor overconfidence vary in the African Stock Markets?
iii. How does the effect of investor overconfidence on stock return volatility conform to the AMH in the selected African Stock Markets?

1.5 Justification for the Study

This study investigated one of the most widely recognised cognitive biases: overconfidence in investor decision-making. It is one of the key hypotheses for active investment schemes and excessive trading (De Bondt & Thaler, 1995). This doctoral research contributes to existing knowledge in many ways. Firstly, it aims to provide a conventional measure, explaining and understanding investor overconfidence impact on investors' financial decision-making in African's stock exchanges. Shah, Raza, and Khurshid (2012) argue that overconfidence bias is mainly believed to create inefficient markets due to mispricing, excessive volatility, and overestimating one's belief in the exactness of price forecasts. Therefore, this study brings in a new perspective regarding investor overconfidence and market efficiency in the face of the relatively new AMH hypothesis.

Secondly, AMH states that investor confidence is not static and can emerge in specific market conditions and vanish in others. This study fills this gap in the literature and examines how investor overconfidence plays out in African stock markets within the AMH paradigm. It assesses whether or not investor overconfidence is normal and adaptive across African equity markets. This study is among the early studies to examine investor overconfidence in the context of the AMH and examine whether this bias appears and disappears as market conditions change in African equity markets. The results are vital for the investing public and stockbrokers in devising appropriate investment strategies. The study also provides essential information to investors about whether the African stock markets simultaneously exhibit similar or different risk and return behaviours in the face of overconfident investors or should be viewed differently. This sheds light on the appropriate investment strategies, trends and models to adopt, taking advantage of any potential profit opportunities while preserving their wealth.

Furthermore, the study also helps clear up confusion regarding the impact of investor overconfidence on market efficiency, whether it creates inefficiency, contributes to greater efficiency, or relates to the adaptive form of market efficiency. Understanding investor overconfidence and its impact on individual decision-making, return volatility, and the stock market helps investment managers set better investment outcomes and establish better client consulting relationships.

1.6 Delimitation of the Study

To ensure feasibility of the research, stay focused on the research aims, and avoid being side-tracked by tangential issues or data, it is necessary to define certain delimitations. This is important because it indicates that the study has delimitations but has sufficient scope to realise the objects of the research. Firstly, the study specifically examined only seven selected African stock markets, namely Casablanca Stock Exchange, Egyptian Exchange, Ghana Stock Exchange, Johannesburg Stock Exchange, Nairobi Stock Exchange, Nigerian Stock Exchange and the Stock Exchange of Mauritius, instead of all stock exchanges in Africa. It could have been possible to choose more from at least 30 stock exchanges. However, the seven selected stock exchanges were considered sufficient in terms of their heterogeneity in geographical location, size, market capitalization, level of market development, economic growth drivers, and overall economic impact for such a study.

Secondly, the data chosen for this study are stock market returns and market turnover. The study embraced the following variables to construct the investor overconfidence index: market turnover, market depth, historical market performance and volatility. Liquidity, confidence intervals, turnover, portfolio risk and diversity level are some of the metrics that could have been used. However, the selected variables were considered appropriate due to the nature of the study, which sought to analyse investors' overconfidence on the market level. In terms of methodology, the study used the Generalised Methods of Moments dummy regression model and the Markov Switching Time Series Vector Auto regression (MS-VAR) model to explore the asymmetric response of market turnover on stock returns in diverse market conditions. The research likewise focused on GARCH models. Other models could have been used, but GARCH models were purposefully adopted, not only because of their demonstrated applicability in examining volatility in literature but also because they enabled the running of rolling window estimations and produced reliable results that account for changes in investors' overconfidence behaviour over time.

1.7 Structure of Thesis

The thesis is organised into six sections.

Chapter One: The introduction and Background to the study

The introductory section outlines background information of overconfidence. Furthermore, the problem statement and key research questions are raised, and the aims are presented. A justification for the study is also presented.

Chapter Two: Conceptualisation and Theoretical Framework

This section provides the necessary and comprehensive review of related literature, providing a theoretical background and conceptual framework for investor overconfidence. It provides an extensive review of EMH, BF and AMH, which are the main philosophies of the behaviour of stock returns. It also provides a theoretical framework for the present study.

Chapter Three: Review of Empirical Literature

This section extends the literature review by looking at empirical studies. It presents conclusions from existing studies on the subject matter and helps to pinpoint research gaps in the literature.

Chapter Four: Research Methodology and Data.

This section describes the research methodology employed to fulfil the research objectives. This is also where sources of data, data collection and statistical analysis tools are presented. The section also describes the various models and tests (Unit root tests, Augmented Dirk Fuller (ADF), Kwiatkowski-Phillips-Schmidt-Shin (KPSS)). The section explains the regression procedure for comparing the varying degrees of investor overconfidence in different stock markets, explains the Generalised Methods of Moments (GMM) dummy regression regime-switching vector auto-regression, and uses several GARCH models like EGARCH and TARCH to model stock return volatility through investor overconfidence and market conditions in rolling windows.

Chapter Five: Results Analysis and Discussion,

The chapter presents a full results analysis and a discussion thereof. The results of the various models estimated are presented. When presenting the results and interpretation, the order of the objectives is followed, and finally,

Chapter Six: Conclusions and Recommendations

This section presents a summary of findings and other important aspects, and a conclusion is drawn based on the decisions reached. The chapter also presents recommendations. The section also provides limitations, implications of the findings and proposals for future research.

CHAPTER 2: CONCEPTUALISATION AND THEORETICAL FRAMEWORK

2.1 Introduction

Standard financial theory is based on the EMH concept introduced by Samuelson (1965) and Fama (1965, 1970). EMH asserts that all available information, historical and public, has been incorporated into the pricing system; therefore, price is the finest indicator for the true value of an investment (Shiller, 1998). Investors are said to be rational; they compete to find abnormal returns and thus push stock prices toward their intrinsic value (Ritter, 2003). The classical school of thought defines rationality as logic. For example, if an investor prefers stock P to stock Q, then stock Q to stock R, it proves that the investor prefers stock P to R, but that is a different case in real life. Many investors disregard the rules of classical thinking and can end up trading too much, buying or selling, when it is not the right time to do so. They let their emotions dictate judgment, underestimate the odds, or pursue performance in vain (Babajide & Adetiloye, 2012). People cannot maintain their rationality for longer periods because they get influenced by emotions, beliefs, and moods (Shah, Raza & Khurshid, 2012). Simon (1957) argued that each individual's reasoning ability is limited within a certain period. Therefore, this explains why investors cannot process information at maximum capacity during problem-solving.

BF researchers have developed numerous inspirational reviews implying that investors sometimes make irrational decisions (Brunnermeier & Oehmke, 2012; Gervais, Heaton & Odean, 2011; Huckle, 2007). These are discoveries of great significance to the development of the stock market. Babajide and Adetiloye (2012) argue that market stability depends on the daily actions of investors trading in the stock market. BF suggests that even with all the necessary elements to make a sound decision (such as statistics, know-how and understanding), investors cannot consistently make the right investment decisions. Lo's (2004) AMH applies evolutionary ideas to economic behaviour instead of the rationalist reasoning of the EMH. According to EMH, no learning or adjustment occurs because it assumes a static market environment. The market is continuously and efficiently balanced; thus, there is no error for investors. The AMH framework recognizes that markets are dynamic; investors make mistakes and learn from them. They adapt their behaviour appropriately, so it is not surprising that a move toward equilibrium is not guaranteed or not likely to happen at any one period as a result of elements like participant entrance and departures or institutional changes (Lo, 2005).

Taylor and Brown (1988) are among the leading proponents of the hypothesis that certain positive illusions are normal and adaptive. They tested hypotheses about uncannily confident self-evaluations, idealistic optimism, and inflated mastery assessments. Their results highlight the importance of these measures when a person feels threatened and receives negative feedback, leading to adaptation. Classical finance tells us what investors should do, and BF tells us what investors actually do (Babajide & Adetiloye, 2012). AMH establishes a link between EMH and BF, showing that they can coexist coherently and intellectually satisfyingly (Lo, 2005).

2.2 Efficient Market Hypothesis (EMH)

The concept of efficient markets originated from Bachelier's (1900) doctoral thesis at the Sorbonne. His results showed that stock prices must necessarily fluctuate randomly. Samuelson (1965) explained why stock prices should fluctuate randomly, and Fama (1965) formalised the EMH by coining the term "efficient market" in finance. In such a market, asset values accurately represent all available information, moving rapidly towards the latest news (Fama, 1965; 1970). Although Fama (1965) proposed the main conceptual view of efficient markets, Samuelson (1965) presented a formal economic argument for efficient markets from the perspective of Martingale rather than a random walk. Starting from Fama (1965), many other researchers have defined an efficient market differently. Malkiel (2003) defines an efficient capital market as one where "prices fully reflect all known information and even uninformed investors who buy diversified portfolios at given prices determined by the market will also earn the high rate of return made by experts". Brealey, Myers, and Allen (2020) define a market as efficient when higher returns than the market return cannot be achieved. Stated differently, the stock's price mirrors the company's fair value which is equivalent to the future cash flows discounted at the alternate cost of capital.

Generally speaking, an efficient stock market is one in which the values of stocks accurately represent reflect the company's fundamental information. In this scenario, the market value of the company grows substantially in line with the business' intrinsic value (Degutis & Novickytė, 2014). The term "efficiency" means that in comparison to other investors, the investors do not have the opportunity to gain excess returns from financial market transactions. They are unable to outperform the market. Therefore, investors can merely achieve greater profits by making investments in riskier securities (Titan, 2015). EMH rejects active portfolio management, arguing that hiring a fund manager is unnecessary because the asset prices already take into account all the information. Roberts (1967) and Fama, Fisher, Jensen, and Roll (1969) found proof supporting the EMH, showing that prices signal all the available information. Although many people have attempted to discover the truth about EMH, there is still no conclusion. There are conflicting views about this hypothesis; for every paper confirming it, another article denies it. This is universally true for all economies, developed or emerging. As a result, it is still unclear whether markets are efficient (Titan, 2015).

Fama (1970) describes in detail three forms of market efficiency: weak form, semi-strong form and strong form, as shown in the diagram below:

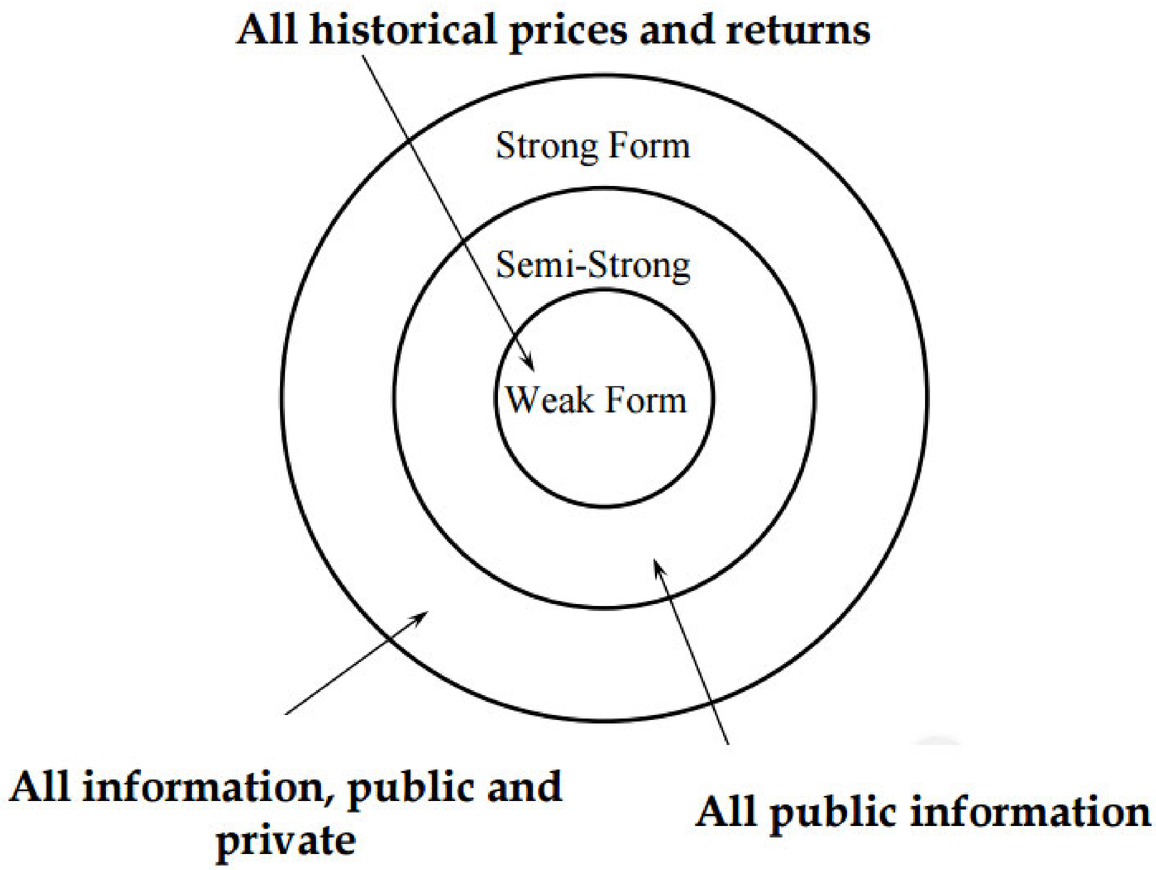


Figure 2.1 The three forms of Market Efficiency

Source: Lin (2016)

In Figure 2.1 above, the circles represent the amount of information contained in each form of the EMH. The weak form includes the least information, the semi-strong form includes any information that is accessible to the public, and the strong form includes all the information. It crucial to remember that every form that comes after is made up of the forms that come before it.

2.2.1 Weak form efficiency

According to Fama (1965; 1970), the weak form of EMH represents a situation in which the present price of financial assets integrates all past financial information available at any point in time. In weak form efficient markets, present stock prices reflect every information relevant to past share price changes. This information includes data on previous prices and trading volumes. The weak form indicates that the asset price represents all past and historical data. So, using candlestick patterns and charts of past prices to forecast future prices is useless. Based on the above information, making excess profits in the stock market is impossible. Consequently, if the market is weak form efficient, technical analysis will not generate any excess returns (Malkiel, 2011). No one can systematically create excess gains through technical analysis, although some forms of fundamental analysis can (Fama, 1965; 1970).

This EMH form implies prices will exhibit random fluctuations. An amazing body of literature has been written about the unpredictability of stock prices. According to the random walk hypothesis it is not possible to forecast future price movements. A rise or decrease on one given day does not always indicate that there will be another increase or reduction the next day. So, it is adjudged that prices are memoryless. Furthermore, this market efficiency type is part of the suppositions of stock and options pricing hypothesis (Palan, 2004). Several empirical research established that various stock exchanges are weak form efficient (for example, Dickinson & Muragu, 1994; Olowe, 1999; Simons & Laryea, 2005; Nisar & Hanif, 2012; Van et al., 2013; Bulla, 2015; Adigwe, Ugbomhe & Alajekwu, 2017; Boubacar, 2021). The Nairobi Stock Exchange was the subject of empirical research by Dickinson and Muragu (1994). They obtained results consistent with weak form efficiency using serial correlations and operational testing. Dickinson and Muragu (1994) compiled a databank of weekly prices of the 30 highly active stocks on the Nairobi Securities Exchange, measured by the number of trading price observations from January 1, 1979, to December 31, 1988. Using run tests and Q-test statistics, they could not discover data that refutes the notion of weak form efficiency. However, they emphasised that more research using different approaches is needed in any market before concluding anything definitive about the weak-form effectiveness. Chan, Gup, and Pan (1997) investigate the theory of weak form efficiency on 18 global capital markets. The data relates to 1962 up to 1992, having 384 monthly observations for every stock price series. The capital markets have been evaluated separately and collectively. They came to the conclusion that each stock exchange they looked at separately was weak form efficient.

Olowe (1999) reached conclusions similar to those of Dickinson and Muragu (1994) after performing an experimental serial correlation analysis at the Nigerian Stock Exchange. Olowe (1999) experimented using monthly data on 59 socks randomly picked on the Nigerian Stock Exchange from 1981 to 1992. He concluded that the Nigerian stock market conforms to the weak market efficiency standards in general Q tests of partial autocorrelation over ten lags in the return data. However, he questions the market's ability to meet higher performance standards due to poor information flow and ineffective communication systems. Maria (2007) analysed the weak form efficiency on prices of the Portuguese stock index of the Lisbon Stock Exchange from 1993 to 2006. Serial correlation and run tests were employed to test the assumption that stock indexes follow a random walk. The tests were performed by means of daily, weekly, and monthly returns over the full sample period. The researcher finds mixed results, but overall results demonstrate that the Lisbon stock market has shifted to random walk behaviour since 2000 with a reduced serial dependence of returns.

Nisar and Hanif (2012) assessed weak form market efficiency in seven exchanges in the Asia-Pacific region, including Nikke N225 in Japan, Kospi Composite in Korea, KSE 100 in Pakistan, All Ordinary ASX in Australia, Hang Seng (HIS) index in Hong Kong, BSE SENEX in India, and Shanghai Composite in China. The study was conducted for data from 1997 to 2011 using statistical tools, including variance ratio tests and run tests. They discovered that the All Regular ASX, the Kospi Composite, the Nikke N225, and the Hang Seng Index (HIS) markets were weak form efficient.

Andrianto and Mirza (2016) tested the efficiency of the Indonesian Stock Exchange between 2013 and 2014. They used daily stock price data collected from the LQ45 index, the Kakarta Islamic index (KII) and the Kompas index 100. Data were evaluated using run tests and serial correlation tests. They note that daily stock prices fluctuate randomly and that stock price movements have no correlation between the previous and current days. These findings demonstrate that the Indonesian Stock Exchange is weak form efficient. Boubacar (2021) conducted an efficient markets test on eight African stock markets, including Botswana Stock Exchange, Bourse Régionale de Valeurs Mobiles (Ivory Coast and other West African countries), Johannesburg Stock Exchange, Lusaka Stock Exchange, Stock Exchange of Mauritius, Nigerian Exchange, Nairobi Securities Exchange, and Uganda Stock Exchange. The results show that only the Uganda Stock Exchange and the Johannesburg Stock Exchange are weak form efficient.

Until the early 1930s, the random walk hypothesis was overlooked by scientists and academics. Following this time in the 1990s, a novel concept known as the behavioural finance emerged. This new hypothesis highlights the impact of investment behaviour which defies the random walk theory. Several writers, including Peng et al. (1994), Lo and MacKinley (1999), Lo, Mamaynski, and Wang (2000), and Horvatic, Stanley, and Podobnik (2011), disagree with the random walk in their work. Peng et al. (1994) applied de-trended fluctuation analysis to refute random walk theory. Their study later confirmed the random walk using the same technique by Horvatic, Stanley, and Podobnik (2011). They studied the possibility of long-term dependence on the market price of financial assets. Their results show that noisy signals in many real-world systems exhibit long-range cross-correlation and autocorrelations. The random walk theory was tested using variance ratio test in studies of Lo and MacKinley (1999) and Lo, Mamaynski, and Wang (2000), with the belief that variance and the holding period must be associated through a linear connection. They discovered a linear relationship linking variability and holding period.

Ball and Brown (1968) used a sample of 2,340 records from 1946 to 1966 of responses to accounting earnings disclosures to demonstrate capital market inefficiencies. EMH was found invalid since share prices adjusted slowly to fresh information in the initial year after the pronouncement. Titan (2015) reports that investigations on the short-term evolution of economic asset prices produced conflicting results. The majority were built on tests to determine how quickly prices change when new information hits the market. The most positive excess return was observed withing the initial three to four months after the pronouncement. Thus, according to Fama et al. (1969), 940 split events from 1927 to 1959 supported the steady correction of prices in stock exchanges. Drew and Noland (2000) analysed the Australian stock exchange and found that directors who actively managed investment funds always achieved returns inferior to the overall market. This leaves EMH with an added obstacle.

Stanculescu and Mitrica (2012) evaluated the 10 most traded equities on the Bucharest stock market as the subject of the study based on a series of data. The authors tested the sample and found it was not stationary, contradicting the random walk theory. Sewell (2012) finds that the weak form of the EMH does not apply in his study of the London capital market, that is, the examination of the Don Jones Industrial Index from 1928 to 2012. This index typically has increasing returns over one year, subsequently declining returns over the next three years. A study by Birau (2013) compares the weak form efficiency for two neighbouring developing markets. The study compares the weak form EMH in the capital markets in Romania and Hungary analysing daily data from January 2007 through December 2011. It analysed the BET and BET-C indices for the Romanian stock markets and the BUX and BUMIX indices for the Hungarian capital market. Both countries have been identified as having inefficient capital markets. The anomalies detected in the Romanian market were larger than those in the Hungarian market during the same period, possibly due to the different maturity levels of the two markets. Birau (2013) reached similar conclusions to Stanculescu and Mitrica (2012) regarding the efficiency of the Romanian Stock Exchange.

The theory of weak-form market efficiency regarding daily returns of Canadian stock market indices was tested by Shiller and Radikoko (2014). Various statistical tests were used, such as the BG statistical test and the runs test, which support the idea that the returns are serially correlated. The overall results refute the notion that the returns of the TSX Index follow a random walk pattern, thus substantiating the idea that the Canadian Stock Exchange is weak form inefficient. In the study by Tamilselvan and Manikandan (2021), the Indian stock market's random walk theory was investigated using unit root testing. The study covers 12 bank stocks listed and actively traded on the National stock market from January 1, 2008, till October 23, 2015, as well as the daily closing prices for the banking industry index. Augmented Dickey-Fuller (ADF) test, Phillips Perron (PP) test and Kwiatkowski-Phillips-Schmidt-Shin statistical test (KPSS test) were used in the study to test market efficiency. The test results showed that the NSE-Bank index and its 12 stocks were weak form inefficient, allowing investors to develop trading methods to gain abnormal profits. They concluded that using a straightforward buy and hold strategy can generate abnormal returns.

Most other publications do not conclude that markets are inefficient, but others produce mixed results. Malkiel (2003) concludes that contrary to what many authors suggest, capital markets are less predictable and more efficient. Furthermore, "there is clear evidence that whatever unusual behaviour of stock prices may occur, it does present portfolio trading opportunities for investors to achieve spectacular returns adjusted for risk." The author argues that capital markets can still operate efficiently despite anomalies, investor irrationality, and quite large price fluctuations. The author believes that most anomalies are usually too small to generate meaningfully positive excess returns relative to the market while offsetting the transaction costs incurred by investors. According to Dragota et al. (2009), it is impossible to rule out the random walk theory. For this study, a sample of eighteen businesses registered between the inaugural listing date and December 2006 on the Bucharest stock market were used. The sample was modified to counteract the impact of the Monday and Friday effects. Konak and Seker (2014) investigated to determine if growth of the FTSE 100 validates the efficient markets theory. They discovered that the FTSE 100 index supported the random walk theory and favoured the weak form EMH from between 2001 and 2009.

Using the daily closing prices of India's NSE and BSE, Jain, Vyas and Roy (2013) investigated the weak form efficiency throughout the global financial crises from April 2005 to March 2010. Statistical analysis was done employing both non parametric and parametric tests. They came to the conclusion that the Indian equity market is weak form efficient, particularly during the global financial crisis. They also noted that investors do not receive extraordinary returns even if they use inside information. Emenike and Kirabo (2018) used both linear and nonlinear models to investigate the Uganda Stock Exchange (USE) for evidence of the weak form EMH in a random walk model context. Preliminary analysis of USE daily returns from September 1, 2011, to December 31, 2016, shows negative skewness, leptokurtosis, and non-normal distribution. The linear model estimates provide evidence of weak form efficiency. However, estimates from nonlinear models provide confirmation that the USE is not weak form efficient. With the rare exception of contradictory results, According to Bapusaheb (2016) developed nations have more efficient stock markets than growing ones like India. The Indian stock market also failed to achieve the weak form efficiency observed in previous studies. Titan (2015) suggests that investor inattention may factor in potential market inefficiencies and delayed price reactions to event notifications. Some argue that this inattention can result in prices underreacting and returns becoming more predictable over time (Titan, 2015). This topic has generated much discussion in the literature, such as Shleifer (2000) and Hirshleifer, Hsu, and Li (2013).

The stock markets' weak form efficiency analysis in industrialised, emerging and developing nations has been the subject of many empirical studies, especially that of Kendal (1953), Fama (1965), Emenike (2009), Alkhatib and Harasheh (2014); Konak and Seker, (2014). Since Fama (1965) introduced the EMH, many studies have been conducted to test its validity. Both developed and developing countries were used to confirm this theory. The conflicting results and changing current market circumstances persuaded Awan and Subayyal (2016) to investigate the Gulf stock market. They used data from 6 Gulf stock exchanges over five years. The study used daily closing stock indices of Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and UAE from January 1, 2011 to December 31, 2015. Autocorrelation and run tests are employed to assess the weak form market efficiency. The results of the parametric test, namely the run test and the auto-correlation test show that the stock prices in all Gulf markets do not follow the random walk model. The null hypothesis of weak form efficiency was rejected because the auto-correlation coefficient was significant at different lags. Awan and Subayyal (2016) and Emenike and Kirabo (2018) note that there is disagreement among researchers on market efficiency due to the different results of many studies. Empirical investigations in developed countries mainly confirm the random walk theory, and most markets show weak form efficiency. Early studies using serial correlation and trading rules maintained that a lot of industrialised economies were weak form efficient. However, empirical research on emerging or developing nations produced inconsistent outcomes. Stock markets in developing countries are generally less efficient than developed countries (Awan & Subayyal, 2016).

2.2.2 Semi-strong form efficiency

Compared to the weak form of the EMH, the semi-strong form assumes that financial asset prices reflect, at any time, all the information in the market, including historical prices and other historical information. This means that this form of efficiency also integrates the weak form of the EMH, and prices change rapidly and unbiasedly to incorporate any new public information introduced to the market (Fama, 1970). In efficient semi-strong form markets, current stock prices reflect not only historical information about prices but also all information currently available to the public, for example, purchase and buyback announcements, dividend payments, and changes in accounting policies (Malkiel, 2011). In semi-strong form, asset prices fully reflect publicly available historical and new information. Therefore, publicly available data, specifically company profits, size, sales, and stock multiples, is ineffective. This implies that fundamental and technical analysis will not generate excessive returns (Fama, 1965; 1970). In case a semi-strong EMH appears in the capital market, neither fundamental nor technical analysis can determine how the investor should allocate his capital so that the return obtained is higher than the return obtained in the random investment case of a financial asset portfolio (Titan 2015). The semi-strong form of EMH implies that stock prices reflect all publicly available information, so it is impossible to make systematic returns by trading based on this information (Fama, 1970).

The results of semi-strong form studies show that the market reaction to news published in developed markets, especially in the United States and the United Kingdom, is rapid and does not leave any room or opportunity for investors to systematically obtain abnormal returns by trading based on information from published reports (for example, Fama et al., 1969; Fleming & Remolona, 1999; Fifield, Power, & Sinclair, 2002). However, relatively little research on the semi-strong form has been conducted in Africa. The results of Afego (2011) show that the Nigerian stock market is inefficient in the semi-strong form. Bhana (1991) and Adelegan (2003, 2009) reached similar conclusions for the Johannesburg Stock Exchange (JSE) and the Nigerian Exchange (NGX), respectively, when examining market reactions to changes in the firm's divided policy in the different markets. Afego (2015) notes that, except for the JSE, all other exchanges remain shallow and illiquid. The inefficiency of these stock markets has important implications for investors, regulators, and policymakers. While it broadly points to the presence of information asymmetry that creates space for profitable transactions for investors, market inefficiencies also imply that allocations of investment resources in the economy are less optimal (Afego, 2015).

Hussain (2011) conducted a study that examined how monetary policy announcements affect the returns of European and US stock indices and how volatility is affected by monetary policy shocks. The findings have shown that monetary policy shocks to stock indexes respond quickly and disappear within 5 to 10 minutes of their announcement, supporting the semi-strong form of the EMH. A study by Manasseh, Ozuzu, and Ogbuabor (2016) tested the consistency of the Nigerian stock market with the semi-strong form efficient market hypothesis using bonus issuance as the information-generating event. Based on daily data, 121 bonus issues were observed and tested during the 2002-2006 period. The stocks tested are classified according to the size of the bonus issue and by the stock price to know the impact of disseminated information on the prices of different securities. Using event study methodology, the market and the market-adjusted models, and vector autoregressive models, the study finds that

information dissemination had a significant impact only in 2002. It also revealed that stock prices respond more quickly to small bonus issues than medium and large ones.
Furthermore, the test between penny stocks and blue chips shows that only penny stocks are significantly affected. The authors conclude that stock prices react immediately, but not very quickly, to publicly available information. This shows that neither technical analysis nor fundamental analysis techniques can reliably generate abnormal/excess returns by consistently beating the market, thus confirming the propositions of efficient market theory. These results contradict those of Olatundun (2003), who considered NGX to be inefficient in the semi-strong form of EMH.

Altavilla, Gurkaynak, Motto and Rugusa (2020) conducted a study to examine how financial markets react to monetary policy signals. The study maps the ECB’s policy communications on yield curve changes and investigates information flows on monetary policy decision dates. An event study approach was applied to the study, and the results showed that different monetary policy measures impact different segments of the term structure of the interest rate, with changes in policy rates mainly affecting the short end of the curve and quantitative easing measures impact more on the long end of the curve. On the other hand, the impact of forward guidance policies peaks at intermediate maturities. A study by Sun (2020) examined the daily reaction of market interest rates to three monetary policy announcements in China. An event study approach was applied to the study, and the results showed that the response of interest rates to announced changes in retail regulated interest rates and required reserve ratios is positive and significant, included in all terms (maturities), but lower at the end of the yield curve. In contrast, market interest rates hardly react to the MPC’s qualitative announcements on monetary policy direction. Therefore, the study suggests that the PBC should build its policy communication quantitatively.

Gbanador (2021) empirically examined how quickly stock prices listed on the Nigerian Stock Exchange respond to monetary policy announcements. The daily All Shares index and 41 monetary policy announcements from 2014 to 2020 are used as a proxy of stock prices and new information, respectively. An event study method was used, and a 21-day event window was constructed. That is ten days before and ten days after the monetary policy announcement, plus the day of the event. The t-statistic determines whether abnormal returns can be obtained due to monetary policy announcements. The results show that abnormal profits cannot be obtained due to monetary policy announcements. This result implies that stock prices adjust rapidly to new information regarding monetary policy rate announcements, making it difficult for market participants to outperform the market. The conclusion is that the Nigerian stock market is quite semi-strong form efficient.

Nickolas, Laws, and Nikos (2000) studied stock market reactions to the announcement of increased cash dividends and bonus issues in the emerging Cypriot stock market. The study concluded that the Cyprus stock market was semi-strong form inefficient. Olatundun (2003) studied the semi-strong market efficiency of the Nigerian stock market through dividend announcements in price adjustments. The daily data includes 595 annual dividend announcements during the period and uses a market model. The results show that excess returns are present and that cumulative excess returns are significant 30 days before and up to 25 days after the dividend announcement. From the results, it is concluded that the Nigerian stock market is not semi-strong form efficient.

A recent study by Yopa, Djenga, Tonmo, and Ndjanyoub (2022) tested the semi-strong form of the market efficiency hypothesis to confirm whether markets adapt quickly to new information, for instance, how the market reacts to political news. The event study method is used to evaluate the speed of stock price adjustment in response to nine political events in the West African Economic and Monetary Union (WAEMU) from 1999 to 2020 for a sample of 25 companies listed on this African regional stock market. News related to political events is analysed for its impact on stock prices. Binder's (1985) multivariate regression model determines abnormal returns. The asymmetric characteristics of events and changes in volatility over time are modelled through EGARCH (1.1). Their results were not consistent with a semi-strong form of EMH. They document the existence of statistically significant average abnormal returns and abnormal price reactions before public announcements of political events. This may indicate that market participants receive or anticipate information before it is disclosed to the public. Furthermore, the adjustment of stock prices to political events is slow. The results of studies on semi-strong market efficiency vary, while the strong form of market efficiency has not been widely studied, and the results suggest market inefficiencies (Mishkin & Eakins, 2012).

2.2.3 Strong form efficiency

The strong form of EMH assumes that prices incorporate all available information in the market, including historical financial information (weak form), all new public information (semi-strong form), and all private information related to financial assets. In its strong form, asset prices fully reveal all historical, public, and private information, so exploiting private inside information cannot generate profitable transactions (Fama, 1965; 1970). If the market is strong form efficient, current stock prices reflect all possible information that is not necessarily publicly available. This form of market efficiency implies that it is impossible to earn excess profits by trading on inside information, which seems unlikely (Malkiel, 2011). On the other hand, some authors argue that a strong form of market efficiency can be achieved because insider trading is illegal (Schwert, 2003; Degutis & Novickytė, 2014). Additionally, Kelikume (2016) notes the strong form of the efficient market hypothesis.

Chang, Zhu, and Pinegar (2002) studied the Hong Kong stock market from 1993-1997 on insider trading using the event study method and the capital asset pricing model (CAPM). They conclude that insiders earn large abnormal profits from trading their companies' stocks. This shows that the Hong Kong stock market is not strong form efficient.

Many studies have been designed to examine the three types of EMH. Most of them invalidate the semi-strong form and the strong forms of the EMH. Financial data do not support these forms, while opinions are divided in favour of the weak form of the EMH, including the rationale random walk theory. Several weak-form studies have shown that abnormal returns are largely due to chance, with the probability of overreaction approximately equal to underreaction, supporting the weak form of the EMH.

2.2.4 Market Anomalies

The EMH has been criticised, especially after discovering some irregularities in the stock market. Here are some of the main abnormalities that have been observed:

a. January effect

The January effect refers to the hypothesis that stock prices tend to increase in January more than in any other month. This refers to the fact that yields in January are higher than in other months of the year. The first researchers to notice higher average returns in January than in other months were Rozeff and Kinney (1976). According to the study using NYSE stocks from 1904 to 1974, the average return in January was 3.48%, compared with just 0.42% in other months. As a result, stock returns in January will likely be higher than in other months of the year (Alagidede & Panagiotidis, 2006; Aylin, 2014). The January effect is the first and most significant calendar anomaly because it significantly impacts the prediction of the stock market direction for the rest of the year (Rossi, 2015). The November effect was not seen until after the Tax Reform Act of 1986 and was documented by Bhabra, Dhillon, and Ramirez (1999). They also found out that since 1986, the impact of the January effect has increased. Jayen (2016) shows that the average mean return in January is much higher than in the other 11 months of the year. Taken as a whole, their conclusion favours an explanation of this effect based on tax-loss selling. The concept of selling at a loss for tax purposes is the basis of one of the proposed reasons for the January effect. According to this theory (tax-loss selling), investors sell underperforming stocks at the end of the financial/tax year to record capital losses. This is done to offset gains from other stocks and reduce the investor's tax liability. Since the financial year ends in December in most countries, selling at a loss causes prices to fall as the year ends.

The January effect will occur as soon as investors start buying back shares in January, causing stock prices to increase (Aylin, 2014). Mazviona, Mah, and Choga (2021) examined the South African stock market to test for the presence of the January effect. Aggregate and sectoral indices of the Johannesburg Stock Exchange (JSE) were examined from 1995 to 2018. Generalized Autoregressive Conditional Heteroskedasticity (GARCH), threshold GARCH (TGARCH), and Exponential GARCH (EGARCH) models were used in the study. The results of the mean equation show a positive January effect for the Basic materials and Top 40 indices, while for the variance equation, a negative January effect is found in the Health care, Technology, Telecommunications, and Top 40 indices.

b. The weekend effect (or Monday effect)

The weekend effect refers to higher-than-normal returns on certain days of the week, often repeatedly throughout the year (Magnus, 2008). This theory suggests that during scheduled breaks from trading, such as during holidays and weekends, the market does not stabilise; rather, they have experienced increased volatility and have been marked by declines. The common observation that stock prices tend to fall on Mondays is known to researchers and market participants. According to the "Monday effect", returns on Monday are often negative and lower than those from Tuesday to Friday (French, 1980). French (1980) examined daily stock returns from 1953 to 1977 and found a trend for returns to be lower on Mondays than on other days of the week. The author claims that only the weekend effect, not the broader closed market effect, is causing these negative returns. Buying stocks on Monday and selling them on

Friday would be a good trading strategy in this situation. According to Singal (2004), short selling is the main reason for the weekend effect. The author argues that short sellers who do not hedge their exposure to more risk are responsible for this effect. And because they cannot carefully monitor their positions outside of trading hours to avoid losses, they become more vulnerable to risk as new information can appear in the market when they cannot trade. These types of investors want to close their position before the end of the trading day, but due to the costs involved, they only do so on Friday. Since the weekend is when there are more hours without trading, leaving their positions open exposes them to greater risk.

Kra, Lu, and Yin (2019) studied the weekend effect in African stock markets during the global financial crisis. They analysed daily stock market anomalies in African equity markets using the two most representative stock index ETFs, that is, Van Eck Vectors Africa Index ETF (AFK) and iShares MSCI South Africa ETF (EZA), each covering a period of at least 11 years, from the period of before the global financial crisis to 10 years into the global financial crisis. The results showed a significant negative effect on Mondays. The K-W test shows the presence of significant negative anomalies on Monday for both indices. Furthermore, the magnitude of negative average Monday returns in South Africa has become much stronger following the global financial crisis. These results highlight the level of market efficiency in one of the world's leading emerging capital markets.

c. Turn of the month

The turn of the month (TOM) effect is one of the seasonal return anomalies observed in the market and is defined as the tendency for stock returns to increase over the period that includes the last trading day of the month and the first few trading days of the following month. The turn of the month, which has much larger returns than the remaining days, is another anomaly noted in the literature. It simply refers to the trend of stock returns during the last and first days of a particular month (Muhammad, Rehana, & Muhammad, 2013). The turn-of-the-month effect is the tendency for stock prices to increase during the last two trading days and the first three trading days of each month. Urquhart (2013) describes the turning point of the month as the existence of solid returns on the last day of the month and the first three days of the following month. It was determined that the liquidity assumption may be responsible for generating the turn-of-the-month effect. This effect was observed in many markets (Agrawal & Tandon, 1994). Agrawal and Tandon (1994) document an increasing trend in stock returns at the TOM in 18 developed markets. According to Ogden (1990), most investors have access to cash flows at the end of the month and are, therefore, liquid. This liquidity encourages them to invest more in stocks, increasing demand and increasing prices, leading to higher profits at the beginning of the month.

As an alternative explanation, Thaler (1987) and Barone (1990) suggest that institutional investors trade more stocks at the end of the month to improve their performance as a form of makeup (that is, window dressing). Maher and Parikh (2013) suggest that this investment activity of institutional traders is the reason behind the TOM anomaly. They found an increase in domestic and foreign investment volume held at the end of the month in the Indian market. Kim (2022) examined the TOM effect in the KOSDAQ market and found that the effect was significant. Using value and equal-weighted portfolios with all the stocks in the KOSDAQ, the researcher found a significant positive TOM effect. Returns on the month's first and last trading days are the highest and significantly positive. The four-day average return between the last day and the first three days of the month, which many researchers previously defined as the TOM period, was also significantly positive in the market. The results also show that individual and institutional traders do not trade or buy more stocks on TOM than the rest of the days. This contradicts existing explanations for increased stock liquidity among individual investors or institutional window-dressing activities.

d. Small firm effect

The small firm effect is a topic of debate among investors and behavioural finance theorists, where it is hypothesised that companies with lower market capitalisations tend to perform better than their larger counterparts. The argument goes that small businesses are more flexible and can grow faster than larger businesses. Roll (1981) describes the small firm effect as an anomalous phenomenon in financial markets often used to explain the higher profits generated by smaller market capitalisation firms than larger market capitalisation firms. One of the first articles on the "small firm effect," commonly referred to as the "size effect," was written by Banz (1981). According to his research covering 1936 to 1975, owning stocks in small-cap companies yielded superior returns. Reiganum (1981) provided supporting data when he reported that the annual risk-adjusted returns for small businesses were 20% greater. If markets were efficient, one would expect the stock prices of such companies to increase to the point where the risk-adjusted returns to potential investors would be considered typical. However, this does not happen. Several empirical studies have shown that small listed companies generate higher average returns than large companies, even when their risk levels are the same (Roll, 1981).

Zhang (2022) empirically studies the relationship between stock returns, outstanding share size, and total market capitalisation of listed companies in the Chinese market from 2010 to 2019. Panel regression analysis is performed on the data collected with the market capitalisation variable as the dependent variable and the monthly return generated by the company's stock as the independent variable. The analysis was performed using STATA analysis software. The analysis shows a positive relationship between market capitalisation and monthly returns generated, which refutes a small firm effect in the selected sample. Overall, the study shows that stock returns of Chinese companies are negatively correlated with company size.

e. Over and under reaction of stock prices to earnings announcements

Empirical research in finance has revealed two sets of omnipresent anomalies: short-term underreaction to news, such as earnings figures, suggesting that prices are only slow to reflect new information and long-term overreaction when stock prices show negative autocorrelations. Russell and Torbey (2002) posit that overreaction to earnings announcements and underreaction to earnings announcements are well-documented phenomena. Data presented by DeBondt and Thaler (1985, 1987) support the idea that stock prices overreact to recent changes in earnings. They report estimates of abnormal stock returns, positive or negative, for portfolios with poor or excellent earnings and stock performance histories. This can be understood as an overreaction of stock price behaviour in the previous period to earnings developments (Bernard, 1993). Zarowin (1989) disputes this interpretation, although De Bondt and Thaler (1990) agree with it. Bernard (1992) reviews evidence that the average initial reaction to earnings announcements is an underreaction, and other evidence interpreted to show that extreme stock price movements can represent an overreaction to earnings. Information presented by Bernard (1992) supports the idea that the initial response is inadequate and should take at least six months to complete. Ou and Penman (1989) and Russell and Torbey (2002) also argue that the market underutilises financial reporting information. De Bondt and Thaler's (1987) and Ou and Penman's (1989) data appear consistent with an overreaction of stock prices to current earnings changes. Both studies provide estimates of positive (negative) abnormal stock returns for portfolios that have historically produced lower (higher) stock price and earnings performance – as if the previous period's stock price behaviour constitutes an overreaction to earnings developments (Bernard, 1992).

Yılmaz (2016) presents a literature review documenting long-term return reversals and continuations of short- and medium-term continuation in returns and assesses the validity of the market efficiency hypothesis based on experimental results from relevant literature. A body of empirical research demonstrates that the stocks with the worst performance (losers) tend to outperform stocks with the best performance in the previous period (winners) over long periods, and this reversal effect is attributed to investor overreaction. Another body of research shows that winners tend to stay winners, and losers tend to stay losers in the short term. This momentum effect is attributed to poor response or underreaction. The phenomena of overreaction and underreaction are examples of potential violations of market efficiency because these ideas assert that one can profit by buying loser stocks and selling winners (contrarian strategy) over the long term or by buying winner stocks and selling losing stocks (momentum or relative strength strategy) in the short term.

2.2.5 Criticism of EMH

Since its inception, the EMH has received much attention and was considered an almost absolute truth in the nineteen eighties. However, many studies have concluded that markets are inefficient, and the EMH is now considered truth on relative terms instead. The EMH fails to explain excessive stock price volatility, investor overreaction, seasonality of returns, and asset bubbles. On the other hand, stock returns are often uncertain (random), and investors cannot consistently earn excess returns (Degutis & Novickytė 2014). Investors' active participation in the stock market implies that they see profit opportunities, which suggests the market is inefficient. If markets were efficient, investors would not trade, analyse stocks or even hire fund managers because no profits would be made, and the market would end up inefficient (Grossman & Stiglitz, 1980). Many studies that have examined the efficiency of financial markets and question the applicability of the EMH (De Bondt & Thaler, 1985; Black, 1986; Lo & MacKinlay, 1988; De Long, Shleifer, Summers & Waldmann, 1991; Neely, Weller & Dittmar, 1997; Hsu & Shiu 2010; Marozva, 2017). These studies provide empirical evidence demonstrating the existence of inefficient margins on markets. DeBondt and Thaler (1985) point out market inefficiencies in terms of market overshooting and argued that people tend to overreact to public company announcements, reflected in the stock price. Furthermore, De Bondt and Thaler (1985) first noted that stock returns in January are generally higher than in other months, which cannot be explained by fundamental information alone. Black (1986) and De Long, Shleifer, Summers, and Waldmann (1991) emphasise noise traders. Black was the first author to define "noise traders", arguing that noise traders could significantly influence market prices. Hsu & Shiu (2010) aggressive bidding, Lo & MacKinlay (1988), Neely, Weller & Dittmar (1997) and Marozva (2017) time-varying risks and returns that are predictability and profitability in financial markets. Rational investors can maintain significant influence despite declining relative wealth levels (Kogan et al., 2006).

The tests conducted on the EMH could not give exact results but rather give different conclusions. Financial economists have no consensus about any of the three forms of the EMH. Some researchers have hypothesised that models do not confirm the EMH because the models themselves are biased and may give erroneous results (Titan, 2015). Although opposition to the EMH grew stronger, several studies still demonstrate the validity of the EMH; Chan, Gup. and Pan (1997) concluded that global stock markets are weak form efficient. Fama (1998) argues that overreaction in the stock market is as common as underestimation and does not lead to inefficiency. Critics have reduced the popularity of the EMH, but the idea of the market efficiency remains relevant in modern finance (Degutis & Novickytė, 2014).

The importance of the EMH in modern financial theory is still debated. Shiller (2013) calls EMH a “half-truth.” The EMH perfectly describes the trading conditions in the modern stock market, as the flow of information and trade execution is faster than ever. On the other hand, some trends in stock prices cannot be explained by the EMH (Degutis & Novickytė, 2014). This has given rise to the development of behavioural finance. In response to criticism, the EMH disciples have argued that although most investors are sometimes influenced by behavioural biases, such as overconfidence, the influence of irrational behaviour in the market is usually insignificant, so it is not important. EMH has the advantage that the invisible hand will always bring prices to their rational levels.

2.3 Behavioural Finance (BF)

Behavioural finance is finance from a broader social science perspective, including psychology and sociology. This is one of the most essential research programs today, and it starkly contrasts much of the theory of efficient markets (Shiller, 2003). This interdisciplinary field is developed in response to the incomplete nature of traditional financial models (Rehman, 2016; Sent, 2004). BF covers heuristics, biases, and other cognitive, emotional, and social factors in decision-making. It analyses values, preferences, choices, beliefs, and expectations and proposes alternative decision-making theories, like the prospect theory (Wilkinson & Klaes, 2018; Pūce, 2019). BF can be divided into micro and macro. Micro-behavioural finance analyses the behavioural biases that distinguish individual investors from the purely rational economic entities – homo economicus – of neoclassical economics. It questions purely rational decision-making and asserts that behavioural biases have a profound impact on decision-making and can lead to suboptimal decision-making and errors that are in contrast with traditional finance. Macro-behavioural finance analyses market anomalies to distinguish financial markets from the efficient markets that traditional finance assumes. At the same time, it questions the informational efficiency of markets and asserts that financial markets are affected by behavioural influences like market anomalies, bubbles, excessive volatility, and limited arbitrage.

During the 1990s, much of the academic debate moved away from econometric analyses of time series on dividends, earnings, and prices toward developing models of human psychology related to financial markets. Researchers have seen too many anomalies with too little inspiration for our theoretical models to capture significant fluctuations. A large body of empirical research, summarised in Campbell, Lo and MacKinlay's 1997 book, The Econometrics of Financial Markets, laid the foundations for a revolution in finance. BF is a study that explains why investors often make mistakes when making investment decisions (Arshad & Sharif, 2018). It illustrates the impact of human psychology on financial decision-making, recognising frequent and predictable individual errors in investing (Huckle, 2007). It highlights inefficiencies due to investors' behaviour. BF explains how the investors actually behave, not what traditional finance claims. This helps describe the 'how' and 'why' markets can be effective (Arshad & Sharif, 2018). In general, the field of behavioural finance has attempted to bring more realism to economic theory (Pūce, 2019). BF investors make irrational decisions influenced by their emotions and beliefs, which creates anomalies in the financial markets that economic fundamentals cannot justify. EMH cannot explain certain anomalies detected in the stock market.

To understand BF, one must understand the structure of various scientific disciplines, the basic concepts of sociology [1], psychology [2] and finance [3] because they are interdependent (Ricciardi & Simon, 2000).

1. Sociology - systematic science about socio- behaviour of human being or a group, emphasising the influence of social relation on people's attitude and behaviour
2. Psychology - a science that analyses processes of behaviour and mind, how physical, psychical, and external environment of human beings influences processes;
3. Finance - a system of formation, distribution, and use of resources.

It combines behavioural and psychological theories with conventional financial theories to explain investors' irrational decisions. Selden (1912) introduced the human psychology influences on the market by suggesting that price fluctuations in the stock market depend on the level of mental capacity of the investor. There were no other studies on BF before the 1960s. Pratt (1964) analysed investors' perception of risk and its influence on the level of investment relative to returns in the stock market. The author's conclusions indicate that self-reported risk and fear are the main factors determining investment levels, not the threat posed by market indices. Tversky and Kahneman (1973; 1979; 1981) drew much attention by introducing the availability heuristic, prospect theory, and framing, respectively. They emphasise the judgmental heuristic whereby investors evaluate the probabilities of events based on their availability. Prospect theory is a criticism of utility theory because expected utility theory does not explain why individuals have insurance while gambling simultaneously. Tversky and Kahneman (1981) showed that presenting a similar case using several techniques causes investors to change their decisions.

De Bondt & Thaler (1985) officially invented BF. They realised the investors' tendency to continually overreact to unforeseen events, leading to weak form inefficiency in the stock market. This BF paradigm, finance in a broader social science perspective, now constitutes an important research agenda that greatly challenges EMH (Metwally & Darwish, 2015). Today, insights from behavioural finance have been applied in areas such as savings and retirement, consumer protection, health behaviour, environmental protection, development, and education (Sunstein & Reisch, 2017; Pūce, 2019). Furthermore, as African equity markets develop in imperfect information, investors, regulators, and other participants need clarity on the stock market's efficiency or inefficiency to avoid short-term collapse (Kelikume, Olaniyi & Iyohab, 2020).

2.3.1 Behavioural biases

Many biases influence decision-making, and these include representativeness, overconfidence, disposition effect, availability bias, loss aversion, over and under reactions, regret avoidance, endowment effect, self-control, herding behaviour, self-attribution, over-optimism, conservatism, limited attention, cognitive dissonance, familiarity biases, mental accounting, framing, *status quo* bias, hindsight bias, escalation of commitment, randomness bias, belief perseverance, gamblers' fallacy, recency bias (Virigineni & Rao, 2017). However, the most common cognitive heuristics or reasons why behavioural finance leads to irrational behaviour are:

1. **Representativeness**

The representativeness heuristic is a judgment based on stereotypes (Shefrin, 2000) in which people try to integrate a new and unknown event into an existing one and thus discover common elements in completely different events. Tversky and Kahneman (1974) suggested that people often evaluate probability “in terms of the degree to which A is representative of B, that is, in terms of the degree to which A resembles B” (Gupta, Preetibedi, & Poonamlakra, 2014). High representativeness is when observations fit the model (Goldberg & Nitzsch, 2001; Virigineni & Rao, 2017). Representativeness bias results from erroneous cognitive framework when processing new information. To help process new information more easily, some investors project results that fit their pre-existing ideas (Pompien, 2016). There are some real-life examples of representativeness observed in financial markets. For example, the assumption that “good stocks come from good companies” is a product of representativeness bias. The argument against this type of reasoning is that if good management practices were linked to stock prices, they would already be reflected in market prices. Another example is the assumption that “growth stocks are better than value stocks” (Kuriakose, 2017).

The study by Guo (2013) examined using an analytical model of a competitive stock market to test the existence of representative heuristic traders in competition with rational traders. Guo (2013) showed that without the presence of noise traders, heuristic traders would be driven out of the market by rational traders due to representativeness bias. Tversky and Kahneman (1974) argue that individuals frequently forecast future estimates for a stock by considering representativeness. Wen and Jianfeng (2011) argue that market investors extrapolate past returns; thus, past revenue growth rates strongly impact asset valuation exploration in the future. The following table describes the biases associated with this heuristic:

Table 2.1 Biases related to the representative heuristics

Biases	Description
Insensitivity to prior probability of outcomes	The prior probability, also known as the base frequency of the outcome, is one of the variables that has no impact on representativeness but is expected to have a significant impact on probability. In practice, prior probabilities are ignored when measuring probability by representativeness.
Insensitivity to sample size	This bias suggests assessing the probability of obtaining a particular outcome from a sample drawn from a particular group. In other words, people evaluate the probability of a sample outcome and the statistical closeness of the sample to the population parameter regardless of sample size.
Misconceptions of chance	People expect a sequence of events produced by a random process to exhibit key characteristics of that process, even if the sequence of events is brief.
Insensitivity of predictability	People are sometimes asked to make numerical predictions about things like future stock prices, demand for a product, or the outcome of a football match. Representativeness frequently makes these predictions.
The illusion of validity	People often make predictions by choosing the outcome that best matches the input. The degree of representativeness or the degree to which the selected results match the input data will determine their confidence level in their predictions with little or no consideration of variables that limit the forecast accuracy.
Misconceptions of regressions	Failure to understand the effects of regression leads to overestimating the effectiveness of punishment and underestimating the effectiveness of rewards. Rewards are usually given when performance is good, and punishments when performance is poor. By regression alone, behaviour is more likely to improve after punishment and worsen after reward.

Source: Tversky and Kahneman (1974)

2. Herding

Herding behaviour bias is due to individuals' tendency to copy a large group's actions, whether or not they make individual decisions. Khanna and Slezak (1998) argue that investors may decide to copy the performance of others instead of acting on their own private data. This type of impact is often called information cascading. The lack of discrimination in choice causes investors to follow the choices of different investors without worrying about the consequences of technical and fundamental examination by experts in the field. Individuals feel the need to gather in groups (herds) and thus develop herd behaviour in decision-making situations. In other words, in the same context, people will do what others do rather than use their information (Banerjee, 1992; Gupta, Preetibedi, & Poonamlakra, 2014).

Herd behaviour can be seen as an opposite tendency to overconfidence in information efficiency. Herding is an explicit intention by investors to ignore their personal information and copy the behaviour of other investors, causing them to trade in the same direction and thus enter and exit the market as a group (Nofsinger & Sias, 1999; Bikhchandani & Sharma, 2001; Virigineni & Rao, 2017). The herding behaviour of investors can be motivated by rational or irrational motives; it can clearly lead to market stress by pushing asset prices away from fair values supported by economic fundamentals, thereby increasing market volatility (Blasco, Corredor & Ferreruela, 2012). Graham (1999) shows that herding often occurs when many individuals make similar moves, perhaps because some people impersonate the actions of others when making investment decisions. Less educated, less experienced, and older investors tend to reproduce (inclination to herding), reducing stock prices (Lu, 2010; Prosad, 2014).

3. Loss aversion

The loss aversion bias means the tendency of people to be risk averse in terms of losses rather than gains (Kahneman & Tversky, 1984). Conservative investors tend to feel the pain of loss more than the pleasure of gain compared to other clients. As a result, these customers may hold on to their losing investments for too long, even when they see no prospect of recovery (Pompian, 2016). Kahneman and Tversky (1979) found that economic agents are more averse to loss than gains relative to an arbitrary standard. The psychological perception of loss is twice as difficult as the gain brings in happiness. Therefore, people are more willing to take risks to avoid losses than to ensure profits. The endowment effect and status quo bias are related to loss aversion. Loss aversion also explains why economic actors respond more to sanctions than rewards (Kuriakose, 2017).

Losses appear larger than gains. Prior gains reduce risk, while prior losses increase risk (Kahneman & Tversky, 1984). People evaluate payoffs based on whether there are gains or losses relative to their status quo position. Kahneman and Tversky (1979) argue that individuals are more concerned with avoiding losses than with the desire to earn profits. Shefrin and Statman (1985) found that individuals sell profitable stocks too early and stay in losing stocks too long. This implies the investor's desire to avoid the suffering caused by a bad investment decision and, therefore, postpone the sale of shares so as not to have to deal with his or her losses. Investors naturally desire to avoid admitting mistakes and losses (Kahneman & Tversky, 1982). Investors are avoiding a market with recent losses due to regret aversion when, in fact, bargain investments may be the most readily available (Virgineni & Rao, 2017). This is related to the idea that individuals adjust to typical income levels, such that subjective well-being is associated with changes in income rather than income levels (Gintis, 2009).

Some studies show that losses are twice as emotionally important as gains. Bodie, Kane, and Marcus (2023) argue that investor behaviour is sometimes considered short-sighted and foolish in that it ignores anything that might happen after the end of a single period, and in this way, all investors plan for a single indistinguishable time horizon. Yechiam and Hochman (2013) find that adding losses can increase the tendency to choose a bet over a safer prospect with lower expected returns. In Ert and Erev (2013), respondents showed lower risk aversion when choosing between different prospects than between gains. Similarly, decisions made from different perspectives across various circumstances show a more reliable choice pattern under risk-neutral conditions than under risk-averse conditions. Moderate investors often avoid taking decisive action because they fear that, in retrospect, the path they chose may not have been wise. Regret aversion can cause moderate investors to be too timid in their investment choices due to losses they have suffered in the past (Pompian, 2016).

4. Availability

In some situations, people judge the class of a development or the likelihood of an event based on how easily the circumstances or events are remembered. For example, one can assess the risk of a heart attack in middle-aged people by recalling such events among one's acquaintances (Tversky & Kahneman, 1974).

Table 2.2 Biases related to the availability heuristics

Biases	Description
Retrievability of instances	When the size of a class is judged based on the availability of its instances, a class whose instances are easily accessible will appear more frequently than a class with equal frequency whose instances have less retrievability.
Effectiveness of search set	Most people judge that words that begin with a certain consonant are more numerous than words with the same consonant appearing in the third position. Indeed, it is easier to find words with the first letter than with the third letter.
Imaginability	Sometimes, it is necessary to evaluate the frequency of a class whose instances are not stored in memory but can be created according to a certain rule. In such situations, people often generate many cases and evaluate frequency or probability based on how easy it is to construct related cases.
Illusory correlation	Illusory correlation is the perception of a relationship between two variables when, in reality, no such relationship exists. When individuals believe that a relationship exists, they are more likely to pay attention to their common occurrence and, conversely, are less likely to remember much when there is no coincidence of events (Chapman, 1967).

Source: Tversky and Kahneman (1974)

5. Overconfidence

It is defined as the tendency of people to overestimate their skills or abilities, that is, to be overconfident in their abilities, knowledge and information received and, as a result, put off poor investment choices; it also refers to people's arrogant attitude towards the stock market (Gupta, Preetibedi, & Poonamlakra, 2014). Overconfidence is best described as unjustified confidence in one's thoughts and abilities, including cognitive and emotional elements. Overconfidence is reflected in investors overestimating the quality of their judgments. Many aggressive investors claim to have above-average stock-picking aptitude; however, many studies have shown that this claim is almost always a mistake. Barber and Odean (2001) show that after transaction costs (but before taxes), the average investor underperforms the market by about 2% per year due to the investor’s irrational belief in his ability to assess the correct value of your investment securities (Pompian, 2016).

6. Mental Accounting

This is the tendency for individuals to allocate their money into separate mental accounts based on a combination of subjective criteria. It refers to the tendency of people to separate their money into separate accounts based on various subjective criteria, such as the source of the money and the purpose of each account (Thaler, 1985; Virigineni & Rao, 2017). Mental accounting is a set of cognitive activities through which economic actors organise and evaluate their financial choices. Thaler (1985) observed that, despite being aware of the fungible nature of money, economic actors divide transactions into separate mental accounts and process payments differently across these accounts. The three steps of mantal accounting include perceiving outcomes, organizing options, and allocating resources to those outcomes. Consumers’ choices and saving methods are strongly influenced by the mental accounts held by economic actors (Kuriakose, 2017). Conservative customers often treat different amounts of money differently based on how they mentally categorise the money. For example, these investors allocate their assets into safe and risky “buckets.” While this behaviour is not generally harmful, returns are almost certainly suboptimal if all assets are considered safe money (Pompian, 2016).

7. Anchoring

In many cases, estimates are made starting from an initial value that is adjusted to arrive at a final answer. The initial value, or starting point, may be suggested by formulating the problem or may result from a partial calculation (Tversky & Kahneman, 1974). The anchoring effect is described as a heuristic performed when making judgments under conditions of uncertainty (Tversky & Kahneman, 1974). During the choice-making process, anchoring occurs when people use some introductory data to make a judgment. Once the accommodation location is determined, various judgments will be made following this anchor and tend to decode other data surrounding this anchor. In numerical prediction, when a suitable value is available, people estimate starting from an adjusted initial value to arrive at the final answer. The adjustments are generally insufficient (Rekik & Boujelbene, 2014; Virigineni & Rao, 2017). Typically, financial professionals use mental decision "anchors" and unusual physical events to assess significance, which is unnecessary because this bias leads to irrational investment decisions.

Conservative investors are often swayed by buying points or arbitrary price levels and tend to stick to those numbers when faced with questions like “Should I buy or sell this investment?” Suppose the stock drops to 75 USD per share from 100 USD five months ago. Normally, a conservative customer will not sell until the price rises again to at least 100 USD/share (Pompian, 2016). The table below presents the biases associated with anchoring:

Table 2.3. Biases related to anchoring heuristics

Biases	Description
Insufficient adjustment	In addition to when subjects are given a starting point, anchoring also occurs when subjects base their estimate on the results of an imperfect calculation.
Evaluation of conjunctive and disjunctive events	According to studies on gambling choice and probability judgment, people tend to overestimate the probability of conjunctive events and underestimate the probability of disjunctive events. To calculate the probability of conjunctive and disjunctive events, the stated probability of the basic event (success at any stage) is a reasonable starting point. The final estimate in both scenarios is still too close to the base event probability because the adjustment from the starting point is generally insufficient.
Assessment of subjective probability distributions	In decision analysis, experts are often asked to give their opinion about a number in the form of a probability distribution, such as the mean value of the Dow Jones on a particular day. To generate such a distribution, one typically asks subjects to choose values for quantities that fall within a certain percentage of their subjective probability distribution.

Source: Tversky and Kahneman (1974)

8. **Hindsight Bias**.

Hindsight bias refers to the fact that the occurrence of an outcome increases its previously perceived probability (ex-ante probability) of occurring. People violate the rationality principle by adjusting their estimates of the ex-ante probability of an outcome that they know has occurred. If, but only if, they underestimate the probability that the actual distribution of observed results is simply the result of sampling error and instead treat the observed results as inexorably reflective of a distinct initial probability distribution (Kelman, Fallas, & Folger, 1998). Hindsight bias can affect the ability to compare new information with previous expectations, causing individuals to confuse their previous expectations with new information. Due to hindsight bias, investors may be overconfident because they believe they are better forecasters than they actually are (Virgineni & Rao, 2017). Hindsight bias distorts investment decisions, and individuals take disproportionate risks due to incorrect predictions of events (Tchai, 2012). Werth, Strack, and Forster (2002) found that an individual's high level of confidence in his or her a priori estimates (estimates made before knowing information about the outcome) and an individual's low confidence in his or her recalled estimates (estimates recalled after receiving the information) would stimulate hindsight bias for the individual.

Moderate clients may be subject to hindsight bias, which occurs when an investor perceives their past investment results as if they were predictable. An example of hindsight bias is investors' reaction to the 2008 global financial crisis. Initially, many people considered the real estate market's performance from 2003 to 2007 to be normal (that is, no symptoms of bubbles), and then said, "Was it not obvious?" when the market crashed in 2008. Hindsight bias gives investors a false sense of security when making investment decisions, encouraging them to take excessive risk without realising it as such (Pompian, 2016).

9. **Self-Attribution (Self-Enhancing) Bias**

Self-attribution bias (or self-enhancement bias) refers to the tendency of people to attribute their successes to their natural talents and to blame their failures on those external influences (Pompian, 2016). For example, let's say someone invests in a particular stock that is increasing in price. Investors believe that price increases are not due to external factors such as economic conditions or the failure of competitors (the most likely reasons for price increases) but rather due to his/her investment savvy. This behaviour is a classic self-enhancement tendency (Pompian, 2016).

2.3.2 Criticism of BF

Although widely recognised and applied, the BF field still faces many criticisms. And the set of criticisms is quite significant and may raise doubts about the field's credibility (Pūce, 2019). A common criticism of the behavioural approach is that, for all its appeal, "it takes a theory to beat a theory" and that no coherent behavioural theory of asset pricing or business acquisitions has yet appeared. Even when such fully specified models exist, they are diverse, even contradictory, making them virtually useless against standard theory (Hong & Stein, 1999). Neither of these behavioural models explains why mispriced stocks with specific characteristics, such as high or extremely high earnings forecasts, are not arbitrated in the aggregate market portfolio (Forbes, 2020). BF has been criticised for having too many behavioural models and lacking unified explanations for many phenomena (Fudenberg, 2006). This critique addresses the issue that behavioural finance contains a wide range of observations, conflicting theories and models about the same phenomenon and a lack of guidance on when to apply each model. Some of the biases recognised in behavioural finance are contradictory, and it is difficult to distinguish which bias prevails in decision-making. For example, people are more influenced by what they see first ("priming" or "anchoring" effect) or by what they last saw ("recency" effect) (Smets, 2018; Pūce, 2019).

Behavioural economics has also been criticised for lacking normative theories (McChesney, 2014). Instead, behavioural models that attempt to reflect reality better are almost exclusively descriptive and primarily used to demonstrate "how people act." But normative theories are certainly needed in science because they are prescriptive, capable of suggesting "how people should act," thereby helping to determine the best decisions to make (Pūce, 2019). Other criticisms arise from the previous two: because there are so many behavioural models and they are descriptive, the field has also attracted criticism regarding its lack of predictive power (Gigerenzer, 1996; McChesney, 2014). Whether the theory produces predictions which are accurate enough or not (Friedman, 1953) has been stated as value in economics for a long time now (Pūce, 2019). However, much of the criticism levelled at behavioural finance does not jeopardize the overall value and importance of the field. While this criticism does not jeopardize the overall value of the field, it certainly needs to be kept in mind in further research and application of behavioural finance (Pūce, 2019).

Table 2.4 Traditional Finance versus Behavioural Finance

Traditional finance *(Based on classical and neoclassical thought)*	**Behavioural finance** *(Interdisciplinary based on psychology)*
Approach – Normative, describe how the real world should work **Methodology –** usually mathematical	**Approach –** Positively describes how the real world works **Methodology –** mainly experimental
People – Rational Theory of rational agent, *homo economicus* Expected utility theory	**People – are not always rational**; there are systematic deviations from rationality. Bounded rationality, heuristics, and biases Prospect theory
Markets – efficient Efficient market hypothesis Modern portfolio theory, mean-variance analysis (expected return, return volatility) Capital Asset Pricing Model (CAPM)	**Markets – are not always efficient; there are systematic deviations from efficiency.** Empirical evidence on over and underreaction, bubbles and stock market crash Crowd psychology, collective behaviour
World – calculable Cannot explain real-world interactions	**World -complex** Based on academic research in cognitive psychology
Continuous dynamic optimization, equilibrium	Emotions, optimism, pessimism, greed and fear govern every decision (under risky conditions, that is, in real life)

Source: (Pūce, 2019)

2.4 Investor Overconfidence

Odean (1998) introduces investor overconfidence as individuals' tendency to overestimate the accuracy of their asset valuation know-how. The concept of overconfidence arose from mental and emotional research in which participants placed too much emphasis on extrapolation skills and the accuracy of the information provided. Armor and Taylor (2002) observe overconfidence as a standard and orderly inclination of investors to be overconfident in future returns. When investors believe they have complete information about future events, they tend to miscalculate when calculating probabilities (Makokha, 2015). This shows that investors really don't have more information than they claim to have (Trejos, van Deemen, Rodríguez and Gómez, 2019). Smith (2005) defines overconfidence as "a subject's average estimate of confidence minus their average accuracy." Therefore, people are overconfident if they evaluate their abilities more positively than their peers (Makokha, 2015). This can also be expressed as an overestimation of the probability of groups of incidences (Razek, 2011; Gentile, Linciano & Soccorso, 2016). Ackert and Deaves (2009) emphasise that overconfidence comes in many different forms: (1) Better-Than-Average Effect, (2) Excessive Optimism, (3) Illusion of Control, (4) Miscalibration. However, other researchers, such as Bar-Yosef and Venezia (2006), distinguish three main types. The first is over-precision (calibration of probabilities). A second type is overestimation or optimism. Researchers have observed that investors have ironic beliefs about tomorrow's events and overestimate their ability to perform well. The third type is better than average or over-placement. Biais, Hilton, Mazurier, and Pouget (2004) suggest that many people see themselves better than how others see them. We tend to rate our abilities and predictions more highly than our peers. This study focuses on the overvaluation of investors in the stock market.

Akerlof and Shiller (2009) consider investor overconfidence to be an apparent bias based on unstable beliefs. De Bondt and Thaler (1995) and Shefrin (2008) consider overconfidence one of the most powerful findings in behavioural research. Shiller (1999) sees it as a positive and persistent sign. Investor overconfidence involves assertive investors underestimating risk while overestimating their abilities (Thaler, 2005). It is documented in various contexts and appears to be a common phenomenon among investors (Lo, 2005). Some notable studies on overconfidence are by Daniel, Hirshleifer and Subrahmanyam (1998), who link overconfidence with price reversals; and Odean (1999); Barber and Odean (2000; 2001); Gervais and Odean (2001); Statman, Thorley and Vorkink, (2006) and Glaser and Weber (2007) in terms of trading volume and lagged returns. Gervais and Odean (2001) argue that high yields (returns) increase overconfidence, motivating investors to trade more. They tested this through a multi-period market model and observed that losses reduce overconfidence. Their results were also confirmed by Metwally and Darwish (2015). Research by Bracha and Donald (2012) shows that overconfident investors emphasise current results by ignoring possible small risks, leading to large losses. Metwally and Darwish (2015) conducted a study to examine overconfidence at the aggregate market level of the Egyptian Stock Exchange from 2002 to 2012. Their results showed a very high magnitude of lagged returns with respect to trading volume. Their results are consistent with Daniel and Titman's (1997) overconfidence and self-attribution theory.

Pompian (2006) argues that being overconfident does not mean a person is incompetent or is lacking in knowledge, but that an overconfident person's judgment does not necessarily mean that they are ignorant, but rather their assessment and judgment of a situation is erroneous and is judged to go beyond the real scenario. Overconfidence largely shapes financial decisions, fostering a market-beating mentality that leads to too many trades, leading to losses (Haigh & List, 2005; Glaser & Weber, 2007), increasing the likelihood of risk-taking (Nosi´c & Weber, 2010) and weakening the spirit of seeking advice (Gentile, Linciano & Soccorso, 2016). The level of overconfidence changes with the returns obtained in the market. High returns increase the level of overconfidence, which encourages investors to trade more (Barber & Odean, 2000; 2001; Gervais & Odean, 2001). According to Zaidi and Tauni (2012), investors exhibit overconfidence when they tend to seek out information that they perceive as supporting their preferred assumptions and overestimate available facts.

Odean (1999) and Barber and Odean (2000; 2001) empirically test the concept of the investor overconfidence hypothesis using data on individual investors from an American brokerage firm. Their results show that overconfidence increases trading volume and significantly reduces investor returns relative to the market. Gervais and Odean (2001) posit that investors' overconfident behaviour will not make them rich or increase their income, but the process of becoming rich makes them overconfident. Metwally and Darwish (2015) point out that because overconfidence is a systematic cognitive bias inherent in many investors, investor behaviour at the market level (aggregate trading behaviour) can be used to check whether an investor is overconfident or not. By applying vector autoregression (VAR) to market-level data, Chuang and Lee (2006) and Chuang and Susmel (2011) observed that lagged returns are positively correlated with current trading volumes and consistent with the overconfidence hypothesis. Some work consistent with Gervais & Odean's (2001) dynamic model suggests that prior performance promotes overconfidence among investors, especially if prior high returns corroborate their personal information. Jlassia, Naouib, and Mansour (2013) also point out that overconfident investors tend to seek risk trade too much, and high trading volume leads to excessive stock price increases, leading to high volatility (Ko & Huang, 2007). These results are also consistent with those of Glaser and Weber (2009) and Chuang and Susmel (2011), whose studies show that investors overtrade risky assets aftermarket gains. Using market returns as a measure of overconfidence in the US market, Statman, Thorley, and Vorkink (2006) find that past market returns positively correlate with market-wide turnover since investors' overconfidence levels change with market returns. Their results confirm the presence of investor overconfidence. These results are consistent with the studies of Glaser and Weber (2007) and Metwally and Darwish (2015) for German and Egyptian stock markets, respectively.

Jlassia, Naouib, Mansour (2013) and Chi (2013) point out that many studies on investor overconfidence have been conducted in the developed markets of the US and Europe, but very few have been recorded in emerging and frontier markets like Africa. As with industrialised markets, with such empirical studies, the results of investor overconfidence are inconclusive. Using market returns and trading volumes on Chinese and Tunisian stock exchanges, Zaine (2013) finds that trading volumes are affected by lagged market returns by several months. Sheikh and Riaz (2012) and Tariq and Ulla (2013) examined overconfidence in the Pakistan Stock Exchange using an impulse response function and found a positive correlation between lagged returns and turnover. They realised that the actions of overconfident investors were leading to volatility in returns. The impulse response function predicts high turnover rates even when returns are zero. Metwally and Darwish (2015) agree with this reasoning and add that the market can correct and plunge investors into losses.

2.4.1 Miscalibration (Over precision)

Miscalibration is a bias in which a person's subjective confidence in their judgments is certainly greater than their objective accuracy, especially when confidence is relatively high (Lichtenstein, Fischhoff, & Phillips, 1982). Overconfidence manifests itself in the miscalibration of subjective probabilities. Specifically, if someone is asked to set an x% confidence interval for the accuracy of answers to a set of questions, appropriate calibration means that the answer is correct about x% of the time. Empirical tests show that the confidence intervals individuals often provide are too narrow, leading to correct answers falling less frequently within the confidence interval than an accurate sense of one's limitation would imply. In Fischhoff, Slovic, and Lichtenstein's (1977) study, events that people believed were certain to happen occurred only about 80% of the time, while events that people believed were unlikely to happen occurred about 20% of the time. People are overconfident if the precision of their estimates is too high or overrepresented. In other words, they might be wrong if they assign too low a probability to an event (Alpert & Raiffa, 1982).

2.4.2 Illusion of control (Overreaction)

The illusion of control is the tendency for people to overestimate their ability to control events, such as feeling that they have control over outcomes that they clearly have no influence over. In other words, the illusion of control overestimates the role of skill relative to luck in determining outcomes. Accordingly, the illusion of control effect describes the tendency for people to behave as if they may have some control over events or outcomes when they do not. Along with optimism bias, the illusion of control is one of the positive illusions (Abreu, 2014). This effect was named by psychologist Langer (1975) and has been replicated in many different contexts: laboratory experiments, observations of behaviour in familiar games of chance such as lotteries, and self-reports of real-world behaviour. Thompson (1999) comprehensively explains why the illusion of control occurs. She argues that people use control heuristics to evaluate how much influence they have over outcomes. Specifically, people use a simple rule to estimate their control over achieving an outcome with two factors:

A person's intention to achieve an outcome and the perceived connection between their actions and the desired outcome (Abreu, 2014).

The illusion of control bias occurs when people believe they can control or at least influence investment outcomes when they cannot. Bold investors with this bias believe the best way to manage a portfolio is to adjust it continually. For example, transaction-oriented investors who accept high levels of risk believe they have more control over their investment outcomes than they actually do because they are "pulling the trigger" with each decision (Pompian, 2016).

2.4.3 Excessive Optimism (Overestimation)

Puri and Robinson (2007) argue that optimists in real life tend to invest more in individual stocks. According to Lee, Miller, Velasquez, and Wann (2013), optimism bias appears to impact stock selection performance in their sample. Their research also shows that this bias is not overrepresented in either gender but has a different impact on the two genders. For men, optimism bias positively impacts holding period return (HPR). Felton, Gibson, and Sanbonmatsu (2010) suggested that optimism bias may lead to different behavioural tendencies in men and women depending on the field. This shows that optimists do not always perform better than pessimists (Kashef, 2017). Researchers found that people overestimate their ability to perform tasks well and are unrealistically optimistic about future events. They expect good things to happen to them more often than their peers, and they are even unrealistically optimistic about completely random events (Bar-Yosef & Venise, 2006).

2.4.4 Better than average effect (Over placement)

In addition to lack of accuracy, investor overconfidence can also manifest as an unrealistic tendency for individuals to believe that their ability, knowledge, and overall capacity to analyse information is above average (that is, better than average). Svenson (1981) found that 93% of American drivers rated themselves as better than average in a study, one of the most famous above-average findings. Cannell's (1989) survey of academic achievement in the United States found that 48 of the 50 US states performed above national standards, while 90% of elementary schools and 80% of secondary schools exceeded the national standards. The frequency with which school systems report their students performing above the national average has been dubbed the "Lake Wobegon" effect (Abreu, 2014). Ackert and Deaves (2009) suggested that the above-than-average effect may be related to motivational and cognitive mechanisms. Regarding motivation, thinking of yourself as better than average improves self-esteem.

At the cognitive level, the performance criteria we most readily think of are often the ones we are best at (Abreu, 2014). People rate their abilities and prospects higher than those of their peers. This refers to the tendency to overestimate performance, either compared to actual performance or the performance of others (Pikulina, Renneboog, & Tobler, 2017). These different forms of overconfidence are interconnected. For example, people tend to be overconfident in their abilities and knowledge. People who are overconfident in their abilities overestimate their influence on outcomes. People who are overconfident in their knowledge tend to think they know more than they do. People who are overconfident in their knowledge tend to set confidence intervals that are too narrow. These people are often more surprised by their mistakes than expected (Abreu, 2014).

2.4.5 Investor Overconfidence Measures

Some human characteristics such as age, gender, and income have been used to shed light on the occurrence of investor overconfidence in several stock markets but to measure investor overconfidence. Some studies mainly used some of the following quantities: (a) confidence interval, (b) stock turnover ratio, (c) actual average number of transactions (Ho, 2011; Trejos et al., 2019), and (d) portfolio risk (Ho, 2011; Tekce & Yilmaz, 2015) and (e) the level of diversification (Tekce & Yilmaz, 2015).

1 Interval of confidence

Blavatsky (2009) posits that, within confidence intervals, researchers prescribe estimates of upper and lower bounds of possible answers around many binary choice common knowledge questions. Respondents are then asked to express their confidence intervals within certain limits based on the significance level reported by the researcher (Langnickel & Zeisberger, 2016). This measure of overconfidence is presented in the literature as the most common, but (Glaser & Weber (2007) urge caution in its use. Confidence intervals have created a hard/easy effect, in which subjects appear well-adjusted to simple questions but are overconfident on difficult questions (Blavatskyy, 2009; Fischhoff, Slovic, & Lichtenstein, 1977). This method requires a questionnaire survey, making it difficult to use for large samples across multiple stock markets.

2 Turnover rate

The stock turnover rate or ratio seems to be an appropriate proxy measure of investor overconfidence. Overconfident investors trade aggressively, increasing their turnover rate (Barber & Odean, 1999; Statman, Thorley & Vorkink, 2006). Recently, trading volume has been used to measure investor overconfidence in several markets. The assumption is that overconfident investors trade aggressively. Statman, Thorley, and Vorkink (2006) found a strong positive relationship between lagged stock returns and the turnover ratio of individual stocks. This also means high stock turnover rates reflect overconfidence (Glaser & Weber, 2003; Statman, Thorley & Vorkink, 2006).

$$\text{Turnover rate (\%)} = \frac{\text{(Number of trades in the period)}}{\text{(Total number of trades over the sampling period)}} \quad (1)$$

The main challenge with this measure is having a similar average turnover rate for each investor, which makes it difficult to rank investors based on the average turnover rates (Trejos et al., 2019).

3 Actual average number of transactions

Ho (2011) introduced this method to classify and rank investors to overcome the disadvantage of the stock turnover ratio. Investors with different trading behaviours are classified into different groups, thereby minimising Type I and Type II errors, making it a perfect substitute for the stock turnover ratio (Ho, 2011).

$$\text{AANT} = \frac{\text{(Sum Number of Shares)}}{\text{(Number of active periods)}} \quad (2)$$

The AANT is obtained by dividing the total number of transactions by the number of months with transactions.

4 Portfolio risk

It can be inferred that when investors develop overconfidence, they become risk-loving. Overconfident investors trade more in risky assets than rational investors (Chuang & Lee, 2006). An increase in portfolio value increases investors' overconfidence, causing them to buy risky assets (Glaser & Weber, 2009). Two proxy variables are used to measure portfolio risk using month-end portfolios.

(i) The percentage of stocks with large market capitalization due to high liquidity and low risk.

$$\text{Monthly Large Cap Ratio} = \frac{\text{(Large MCap Stocks in the Portfolio)}}{\text{(Total Stocks in the Portfolio)}} \qquad (3)$$

If our calculations give a low ratio, then the portfolio is risky. Assuming the portfolio consists of 4 assets (W, X, Y, Z) and three (W, X, Y) are large capitalisations, the ratio is 75%.

(ii) The proportion of the shares from stocks with small market capitalisations, as smaller companies are considered high risk.

$$\text{Monthly Small MCap Ratio} = \frac{\text{(Small MCap Stocks in the Portfolio)}}{\text{(Total Stocks in the Portfolio)}} \qquad (4)$$

If this ratio is high, the portfolio is risky. Considering the volatility of returns, Trejos et al. (2019) find that large-cap stocks have lower volatility than small-cap stocks, implying less risk than smaller companies.

5 Diversification

The literature shows that individual investors reduce their asset holdings when portfolio turnover increases (a sign of overconfidence) (Glaser & Weber, 2009). Overconfident investors tend to hold diversified portfolios (Odean, 1998). This suggests that diversification can be used as a measure of overconfidence. Tekce and Yilmaz (2015) use a simple way to measure diversification using the average number of stocks in the portfolio.

2.5 Adaptive Markets Hypothesis (AMH)

Authers (2018) posits that the 2007/2008 global financial crisis caused scholars and researchers to abandon attempts to model markets using mathematics or physics, as these methods had become obsolete. It is now more elegant to incorporate biological or medical analogies to model financial markets (Sherlock, 2018). Lo (2004) proposed a new theory, the Adaptive Markets Hypothesis (AMH), that attempts to reconcile EMH and BF. According to AMH, the EMH and investor overconfidence (market inefficiency) can coexist in an intellectually consistent manner. Using evolutionary principles such as natural selection and adaptation to financial connections, the AMH reconciles market efficiency with behavioural alternatives. Lo (2005) points out that behavioural biases such as investor overconfidence have become important in the evolutionary model of members adapting to dynamic environments through simple heuristics.

The AMH's ideas were motivated by Nobel laureate Simon's (1955, 1982), bounded rationality Wilson's (1975), evolutionary biology, Mangel and Clark's (1988) behavioural ecology, Pinker's (1997) evolutionary psychology and Farmer's (2002), complex systems (Lo, 2005). Lo (2005) argues that individuals are inherently rationally bounded but do not take an evolutionary perspective into account. AMH thus arises from the combination of bounded rationality and satisficing. From an evolutionary perspective, natural selection controls the point at which optimistic investor behaviour is satisfactory (Lo, 2004). Some investor choices depend on "best guess" and past experience about the possible optimal level derived from the feedback received. If the economic environment is static, investors gradually develop optimal solutions. However, in the case of a change, these solutions are unsuitable for the new economic situation, leading to behavioural bias (ill-advised actions). Such behaviour is not irrational but rather called "maladaptive" because suboptimal behaviour is rational once we take the heuristic outside the evolutionary context (Lo, 2004). The AMH notes that investment strategies go through cycles of losses and gains due to fluctuations in the trading environment, the level of profit opportunities available at any given time, and the level of competition (the number of investors) in the market. Investors act accordingly to any changes in these variables.

Several studies have been conducted to test whether the efficiency of different markets is consistent with the AMH. Obalade (2019) examined daily data from several African markets from 1998 to 2018 and found that market efficiency evolved cyclically over time, according to the AMH. Noda (2016) examined the Japanese stock market and found that market efficiency fluctuates over time, according to the AMH. Zhou and Lee (2013), using automatic variance ratio and portmanteau testing, studied Real Estate Investment Trust (REIT) data and found evidence of time-varying market efficiency and market conditions, as stated by the AMH. The work of Urquhart, Gebka, and Hudson (2015) examines the moving average (MA) rule of the US, UK, and Japanese markets, and it reveals that trading strategies based on signal anticipation generate higher gains. Therefore, investing in future indicators represents a reasonable explanation of the price reaction to future indicators consistent with the AMH. Urquhart and Hudson (2013) found evidence of the AMH in the UK, USA and Japanese stock markets using very long data through linear and non-linear controls for independence of price returns. Their evidence supports the AMH and suggests that the AMH is better than the EMH in explaining stock return behaviour.

2.5.1 Implications of AMH

AMH has several implications, as Lo (2005) points out. The first implication of this new world order is that the risk-reward trade-off balance between risk and return may no longer exist (Lo, 2017). This implies that if a relationship between risk and return exists, it is unlikely to be stable over time. Such relationships are determined by the relative sizes and preferences of different market ecosystem populations and institutional aspects such as the regulatory environment and tax laws (Lo, 2005). Because these factors change over time, any risk-return relationship can be affected. A consequence of this implication is that the equity risk premium is not a universal constant but varies over time and is path-dependent. If risk preferences change over time, the equity risk premium must also change. A complementary idea of the AMH is that overall risk preferences are not fixed but are continuously shaped and reshaped by the forces of natural selection. In this context, natural selection determines who participates in market interactions. Investors who suffered significant losses during the tech bubble are more likely to have exited the market, leaving today's investor base significantly different from four years ago. Regardless of whether prices fully reflect all available information, the specific path that market prices have followed in recent years will influence current aggregate risk preferences (Lo, 2005).

A second implication is that, unlike traditional EMH, arbitrage opportunities sometimes exist in the AMH. Without such opportunities, there would be no incentive to gather information, and the price discovery aspect of financial markets would collapse (Grossman & Stiglitz, 1980). Therefore, unlike the EMH, which argues that active management is worthless and cannot outperform a “buy and hold strategy”, the AMH justifies active portfolio management. (Lekhal & Oubani, 2020). From an evolutionary perspective, dynamic and liquid financial markets imply that profit opportunities must exist. When exploited, they disappear (Lo, 2017). But new opportunities are also constantly being created as some species disappear, others appear, and institutions and economic conditions evolve. Rather than the inevitable trend toward greater efficiency predicted by the EMH, the AMH involves significantly more complex market dynamics, with cycles and trends, panics, manias, bubbles, crashes, and other phenomena frequently observed in natural market ecosystems (Lo, 2005).

Thirdly, investment strategies would also experience ups and downs, with good results in some environments and poor results in others. Unlike the classical EMH in which arbitrage opportunities are introduced to competition, ultimately eliminating the profitability of strategies designed to exploit the arbitrage, the AMH implies that such strategy may decline for some time and then return to profitability as environmental conditions become more favourable for such arbitrage trading (Lo, 2005). The effect of this implication is that market efficiency is not an all-or-nothing condition but a characteristic that continuously changes over time and across markets. Convergence towards equilibrium is neither guaranteed nor possible, and it would be inaccurate to assume that markets must evolve towards an ideal efficient state (Lo, 2005). Lastly, the implication of the AMH for asset allocation is that characteristics such as value and growth from time to time can sometimes behave like risk factors. That is, portfolios with such characteristics can generate higher expected returns when these characteristics are favourable (Lo, 2005). This means that value and growth assets can generate higher returns in the future when these attributes are favourable. For example, growth stocks outperformed value stocks during the US technology bubble of the 1990s and reversed the bubble burst. Such non-stationarity poses a major challenge to the EMH, whether a trait is a risk factor, but the AMH has not yet determined what might constitute a risk factor (Lo, 2005). How a particular characteristic is valued depends on the nature of the investor group at any given time. If a significant portion of investors prefer growth stocks over others, then the risk premium associated with the growth factor will emerge. As the number of growth-oriented investors declines, either because they retire and withdraw assets from the stock market or because a new generation of investors enters the stock market with their own preferences, the growth premium will decrease, and other traits may emerge to replace it (Lo, 2005).

2.6 Conceptual framework

EMH claims that all past information is fully reflected in the current stock price, so technical and fundamental analyses are fruitless in an efficient market. There is no need to actively trade in the stock market, so past market returns do not affect the investor's trading activity. BF assert that behavioural biases such as investor overconfidence indicate an inefficient market. AMH posit that changing conditions cause markets to fluctuate between efficiency and inefficiency. These relationships are illustrated in the diagram below.

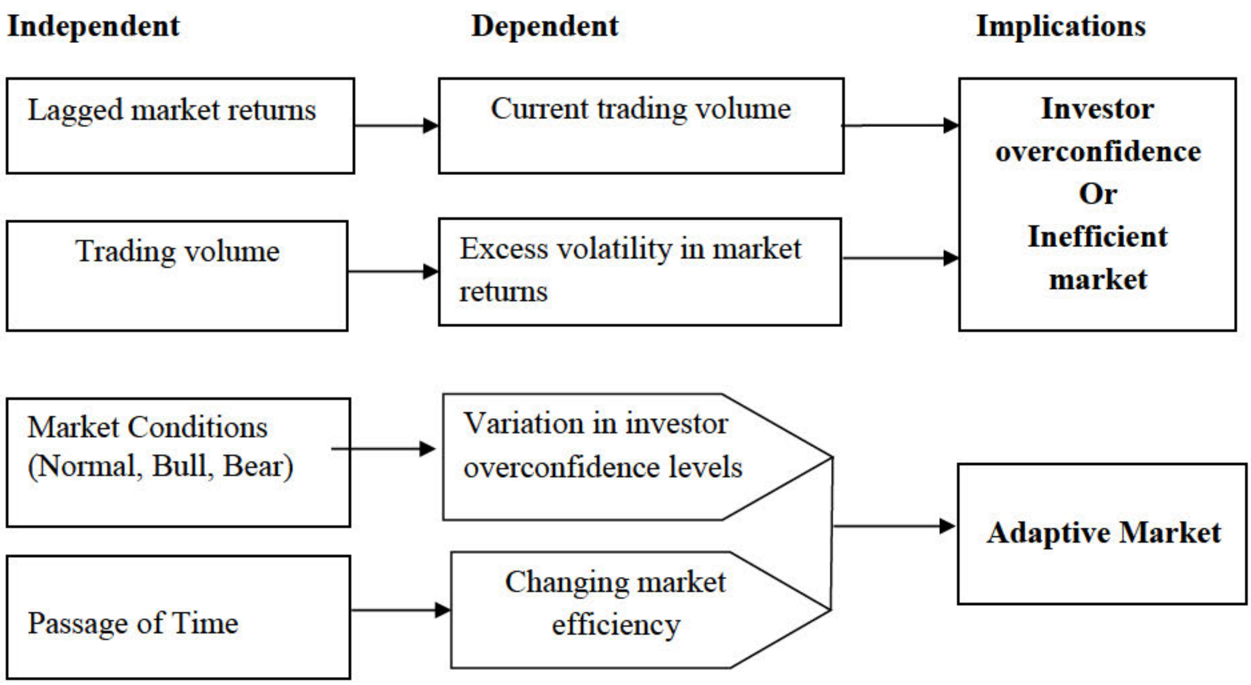


Figure 2.2 Investor overconfidence, market efficiency and Adaptive Markets Hypothesis

Source: Author (2023)

The figure above shows that if the current trading volume depends on the lagged market returns, investors are overconfident, and the markets are inefficient. For the same reason, if excessive volatility results from high levels of trading, then the market is inefficient. If investor overconfidence is affected by changes in market conditions, then it follows the AMH. Furthermore, if there is a change in market efficiency or investor overconfidence changes over time, the market is said to be adaptive.

2.7 Summary

The EMH assumes that investors are rational. They compete to seek abnormal returns and thus push stock prices towards their intrinsic value so that stock returns are unpredictable. Therefore, it is impossible to beat the market, and no investor can predict future stock market returns better. Despite widespread criticism because of many observed patterns, such as excessive trading, that rational theory cannot explain, the EMH remains an important theory in academic finance literature. These observed market puzzles led to the development of BF, a finance discipline within a broader social sciences perspective, including psychology and sociology, and one of the world's largest and most vital research programs today. It is in sharp contradiction to much of the assumptions of the efficient market theory. BF suggests that even with all the necessary elements to make a sound decision (such as statistics, know-how and understanding), investors cannot consistently make the right investment decision.

Scholars and researchers have sought to move from modelling markets using mathematics or physics to incorporating biological or medical analogies to modelling financial markets. This led to the development of the AMH of Lo (2004). The AMH framework recognises that markets are dynamic and that investors make mistakes and learn from them. AMH argues that investor overconfidence develops cyclically over time and as market conditions change. To this end, investigating and modelling investor overconfidence should be considered based on changes in time and market conditions. The following chapter presents an overview of empirical studies on investor overconfidence as a function of variations over time and market conditions.

CHAPTER 3: REVIEW OF EMPIRICAL LITERATURE

3.1 Introduction

While the previous chapter discussed the theoretical underpinnings of the investor overconfidence bias, the current chapter reviews existing empirical research conducted on the investor overconfidence bias. Several behavioural finance models based on the investor overconfidence hypothesis have been proposed to explain anomalous outcomes, including short-term continuation (momentum) and long-term reversals of stock returns, high trading volume, excessive volatility and a disproportionate amount of risk taken by the investors (Chuang & Lee, 2006; My, Toan & Cuong, 2016). The argument is whether market gains cause overconfident investors to trade more aggressively in later periods and whether overtrading by overconfident investors in the stock market contributes to the observed excessive volatility. Many empirical investigations have been conducted, and it is impossible to determine whether investor overconfidence is static or varies with time and market conditions. The first part of this chapter presents the findings of several existing studies on investor overconfidence in the stock market from an absolute perspective. The second section presents empirical evidence on investor overconfidence in the AMH. Finally, a gap in the empirical literature is also identified.

3.2 Empirical studies on investor overconfidence

Several empirical studies have been conducted to examine the presence of investor overconfidence in developed and developing stock markets. Many researchers have attempted to develop theoretical models based on the investor overconfidence hypothesis to account for the observed market anomalies. They characterise the investor overconfidence hypothesis by assuming that market gains cause overconfident investors to trade more aggressively in subsequent periods (Statman, Thorley, & Vorkink, 2006; Chuang & Lee, 2006; Chuang & Susmel, 2011; My, Toan & Cuong, 2016). The excessive trading by the overconfident investors in the stock market contributes to the excessive volatility observed. Overconfident investors underestimate risk and trade more in risky securities (Chuang & Lee 2006). This empirical examination presented below considers three types of markets, namely developed markets, emerging markets and the African markets.

3.2.1 Investor overconfidence from developed and emerging markets

Studies on the developed markets constitute the largest body of literature on investor overconfidence. Odean (1998) was one of the first studies to examine the impact of investor overconfidence on financial markets. Odean (1998) suggests that trading volume increases when price takers, insiders, or market makers are overconfident. Statman, Thorley, and Vorkink (2006) tested Odean's (1998) proposal by examining whether the level of investor overconfidence (proxied by trading volume) fluctuates with lagged market returns or not. The test was performed on all common stocks traded on the New York Stock Exchange (NYSE) from August 1962 to December 2002 using a vector autoregression (VAR) model and impulse response functions. They note that, besides the investor overconfidence explanation, there may be other explanations for the lead-lag relationship between trading volume and market returns. For example, significant changes in asset prices can encourage investors to rebalance their portfolios, thereby boosting trading activity. Gervais and Odean (2001) argue that investors learn about their abilities by observing past successes and failures. Kamesaka, Nofsinger, and Kawakita (2003) suggest that investor overconfidence may be associated with positive feedback trading (trading in the direction of past patterns). Indeed, if certain events confirm the reliability of an investor's trading model, this investor would feel openly proud that the strategy he has chosen is correct (Odean, 1999). Chou and Wang (2011) argue that an investor would be more confident when his success is higher than usual. As such, bull market periods tend to be followed by periods of increased market trading. Therefore, a positive lead-lag relationship between trading volume and market returns is evidence of investor overconfidence (Gervais & Odean, 2001; Statman, Thorley & Vorkink, 2006; Chen & Sabherwal, 2019).

Following the path of Statman, Thorley, and Vorkink (2006), Chuang and Lee (2006) conducted a study testing the investor overconfidence hypothesis using aggregated data from all firms trading on the AMEX and NYSE from January 1963 to December 2001. Their results reveal several important empirical findings. Using a moving average model to observe how stock prices react to information (public and private), they found that overconfident investors overreacted to private information but underreacted to public information. Chuang and Lee (2006) also used bivariate Granger causality tests to study the causal relationship between trading volume and returns. Their results show that market returns Granger causes trading volume and thus positive market returns leading to excessive trading by overconfident investors in the periods following positive market gains. This result is in line with the studies of Gervais and Odean (2001), Statman, Thorley and Vorkink (2006), Chuang and Susmel, 2011

My, Toan and Cuong, 2016 Chen and Sabherwal (2019), who also argue that the positive relationship between market returns and trading volume reflects investor overconfidence.

Bouteska and Regaieg (2018) studied the effects of two behavioural biases, namely loss aversion and overconfidence, on American companies' performance. The study used approximately 6,777 quarterly observations of the number of insured industrial and service businesses in the United States from 2006 to 2016. Ordinary least squares (OLS) regression in two-panel data models was used to test the hypotheses formulated for the study. Loss aversion bias has been shown to harm the economic performance of businesses in both sectors. On the contrary, the results show that overconfidence positively affects performance in the industrial enterprise market but negatively affects performance in the service enterprise market. Further strong evidence is found that the overconfidence bias appears dominant, and investors may be more overconfident than loss-averse.

Zia, Sindhu, and Hashmi (2017) explored the existence of investor overconfidence in the Pakistani stock market from 2005 to 2013. Unit root test, VAR, impulse response function, and Granger causality tests are some of the econometric techniques used in the research. A security level panel VAR model was used to assess how current market turnover is related to lagged market returns. The regressed VAR models demonstrate that, for most observed stock markets, a strong and positive relationship exists between current turnover and past stock returns of the respective markets, thus indicating the presence of investor overconfidence. Zia, Sindhu, and Hashmi (2017) found out that the current day's trading volumes are significantly affected by the stock returns of previous days and thus indicate the presence of investor overconfidence. Furthermore, the results of the impulse response functions demonstrate that historical market returns positively confirm current market turnover.

Griffin, Nardari, and Stulz (2007) studied the dynamic relationship between market-wide trading activity and stock returns in 46 countries. Many stock markets show a strong positive relationship between turnover and past market returns. This relationship is much stronger for developing countries than for developed countries. These results hold when they control for stock market volatility, alternative definitions of turnover, and different sample periods, and they occur at both daily and weekly frequencies. They also found out that the relationship is more economically and statistically significant in countries where short selling is restricted, corruption is higher, and the allocative efficiency of stock markets is lower. The return volume relationship is also stronger for individual investors than for institutional or foreign investors. Prosad, Kapoor, and Sengupta (2013) found that biases such as the disposition effect and investor overconfidence are prevalent in the Indian stock market and can lead to increased trading volume at the market and individual securities levels.

Gupta, Goyal, Kalakbandi and Basu (2018) examined the impact of investor overconfidence in the emerging stock markets of India and China. Their study examined the existence of the investor overconfidence bias before, during and after the 2008 subprime financial crisis and therefore, the study period from April 2001 to March 2016 was divided into subsamples to account for the pre-recession period (April 2001 to June 2007), during the recession (July 2007 to December 2009) and after the recession (January 2010 to March 2016). Following the model by Statman, Thorley, and Vorkink (2006), the study uses a VAR model to investigate the relationship between current turnover and lagged market returns. Regression VAR models for the entire sample indicate that, in each market, the current market turnover depends on the past market returns, and thus, the results support the hypothesis of investor overconfidence. Additionally, Gupta et al. (2018) found out that the Indian investors were less overconfident than the Chinese investors.

Chen and Sabherwal (2019) studied stock options traded in the United States from 1996 to 2015. Their objective was to evaluate whether high trading activity observed in the options market was related to investor overconfidence. They used ordinary least squares regression to examine the relationship between options volume and lagged stock returns. In options markets, investor overconfidence may develop gradually and thus does not easily dissolve (Chen & Sabherwal, 2019). Therefore, they argue that lagged cumulative market returns are a more relevant proxy for investor overconfidence than individual monthly returns. They found out that historical stock market returns have a strong positive impact on the trading activity of options investors. This illustrates the presence of investor overconfidence in the options market.

Prims and Moore (2017) presented a study examining the correlation between different forms of investor overconfidence and age. The study used a survey methodology created on the Amazon Mechanical Turk platform. A sample of 200 participants aged 18 to 75 years were interviewed. An exploratory test was conducted in which age was correlated with a measure of three different types of investor overconfidence, with the results then replicated. The research showed that a lifetime of experience, instead of leading to better decision-making, increases their confidence levels. Aharon and Qadan (2018) studied how US investors' confidence levels affect their commodity information needs. Using the sample period from January 2004 to February 2017, Aharon and Qadan (2018) find that their results are consistent with the overconfidence hypothesis, which suggests that overconfident investors trade asymmetrically between gains and losses. A study by Bayyurt, Karisik, and Coskun (2013) surveyed 2,036 Turkish investors in 2013 to examine differences between women and men in their personal investment preferences, using a discriminant analysis and logistic regression. The results indicate that male investors prefer to invest in common stocks and real estate, while female investors are more risk-averse and prefer to invest in gold and fixed deposits. This shows that men show higher levels of overconfidence than women. Barber and Odean (2001) used gender as a proxy for overconfidence. They confirmed that overconfident men in their sample traded more than women. As a result, men's performance is more negatively affected by excessive trading.

More recently, Alsabban and Alarfaj (2020) examined the presence of investor overconfidence in the Saudi Arabian Stock Exchange (Tadawul) by analysing monthly data for 172 stocks from January 2007 to December 2018. They used a model previously employed by Statman, Thorley, and Vorkink (2006). Specifically, Alsabban and Alarfaj (2020) study the presence of investor overconfidence by examining the interaction between market turnover and market returns using a VAR model and also analysing the market's impulse response. The results obtained by Alsabban and Alarfaj (2020) confirm the presence of investor overconfidence because there is a positive and statistically significant association between current market turnover and historical market returns. Additionally, Granger causality tests show a unidirectional Granger causality between lagged market returns and current market turnover, and impulse response functions show a positive and significant response of market turnover to lagged market returns. Lin, Rahman, and Yung (2010) note that portfolio managers view REITs as an asset class distinct from common stocks. Therefore, Lin, Rahman, and Yung (2010) aim to confirm the overconfidence hypothesis in the REIT market. To achieve this goal, the researchers analysed the monthly returns of all REITs found in the Centre for Research in Security Prices (CRSP) database over the study period from January 1990 to December 2006. The study uses an experimental model similar to that of Statman, Thorley, and Vorkink (2006). Accordingly, the main analytical tools of the study include VAR models and their associated impulse response functions. The regression VAR model demonstrates that after controlling for general market overconfidence, current REIT turnover is positively and significantly affected by REIT return, thus indicating overconfidence from REIT investors.

Huisman, Van der Sar, and Zwinkels (2012) present an alternative approach to measuring overconfidence using unique survey data on investors' stock market forecasts. They apply Parkinson's estimates based on extreme bounds around stock market forecasts to infer investor confidence. The results support overconfidence. Daniel, Hirshleifer and Subrahmanyam (1998) propose a model of investor overconfidence that overestimates the precision of their private signals and shows that investor overconfidence leads to negative serial price correlation (price reversal). They overestimate the extent to which they are responsible for their own success, while the stock market's underreaction and overreaction follow public and private signals, respectively.

3.2.2 Investor overconfidence in African markets

Zaiane and Abaoub (2009) examined the effect of investor overconfidence on investor decisions in the emerging Tunisian stock market from January 2000 to December 2006. Consistent with Statman, Thorley, and Vorkink (2006), the research used the VAR model and related impulse response functions to examine how lagged market returns are correlated with current trading activity. They used shares traded as a proxy for trading volume and found little evidence that investors are overconfident in the Tunisian stock market. Adel and Mariem (2013) studied the impact of investor overconfidence on investment decisions. They found that the results demonstrate the importance of bias on confidence in analysing the characteristics of the Tunisian financial market. The purposive sampling technique selected 27 companies actively trading on the Tunisian Stock Exchange between 2002 and 2010. Multivariate time series analysis through the application of experiments time series and VAR models, ARMA and EGARCH show that overconfidence bias has a significant positive impact on stocks in Tunisia.

Onsomu (2014) conducted a study on the impact of behavioural biases on investment decisions in Kenya. It was found that the overconfidence bias did not significantly impact as less than 50% of investors were affected. There were no significant correlations between overconfidence bias, availability bias, confirmation bias, representativeness bias, disposition effect, and gender. Indeed, the P value obtained is greater than 5%. Descriptive statistics were used with Pearson's chi-square technique to analyse the data. Onsomu (2015) sought to determine the impact of age on investor decisions at the Nairobi Securities Exchange using 57 respondents from January to March 2014 and Pearson's chi-square method. The results highlight a significant relationship between age and overconfidence bias. Investors aged 18 to 30 were most affected, while those aged 31 to 40 were least affected. This contrasts with Zaidi and Tauni (2012), who found an insignificant relationship between age and overconfidence bias at the Lahore Stock Exchange.

Dowie (2014) examined investor confidence in a sample of South African researchers from selected universities regarding the predictability of mutual fund returns. A total of 407 observations from 41 participants were obtained. Comparing the difference between the fund's return and the investor's return estimate, the results show that investors lacked confidence. The averages of estimated and actual fund returns differed significantly; investors have underestimated their fund's returns rather than overestimated them. Additionally, women underestimate their results more than men. This is consistent with the literature showing that men display more overconfidence than women. Willows and West (2015) assessed whether behavioural bias manifests differently by gender. Using the sample period from January 2007 to December 2011, the trading behaviour of individual investors in South African investment companies is analysed. The Wilcoxon rank sum test results show that men trade more than women. According to Willows and West (2015), this result is consistent with the findings of Barber and Odean (2001), who reported that overconfidence is more common in men than women.

Willows and West (2015), who analysed investor performance in South Africa based on gender, found results consistent with those of Dowie (2014). The investment behaviour and returns of 19,021 investors from South African households were studied from January 2007 to December 2011. Willows and West (2015) claim that men have a higher variance of realised returns and trade more frequently than women. As described in previous literature, overconfident investors tend to trade with higher frequency and make riskier investments, which often leads to variances in returns. The study concluded that investor overconfidence is more common among men, who demonstrate higher risk tolerance and greater self-efficacy. Dowie and Willows (2016) examined the level of investor overconfidence among South African unit trust investors. Their data collection process involved sending surveys to South African university employees investing in unit trusts. The Wilcoxon sign test was used to analyse survey responses to check for overconfidence in investors' estimates of their fund returns. The results indicate that investors underestimate their fund returns rather than overestimate them. Therefore, Dowie and Willows (2016) concluded that South African unit trust investors are underconfident. According to the authors, these conclusions can be explained by the fact that at the time of the study, the 2008 subprime financial crisis was still fresh in investors' minds (Dowie & Willows, 2016).

3.3 Empirical studies on investor overconfidence under AMH

This section reviews the research conducted on investor overconfidence in the context of the AMH. Except for a few, no studies have specifically examined overconfidence in the AMH in Africa. However, these studies can be used to indicate how investor overconfidence affects different markets. The lack of empirical research on investor overconfidence tendencies in African markets highlights the need for research on this topic in Africa.

3.3.1 Time-varying Investor Overconfidence Studies

Confidence develops over time as people receive feedback on their judgments and decisions. When people know that their recent predictions are correct, they tend to adjust their confidence upward; when they learn that they are wrong, they tend to adjust it downward (Daniel & Hirshleifer, 2015). Gervais and Odean (2001) developed a model that describes both the process by which traders learn about their abilities and how bias in this learning process can create overconfidence among investors. The level of overconfidence expected of an investor would increase early in their career, and then, with more experience, they would better realise their abilities. Daniel and Hirshleifer (2015) integrate the dynamics of investor overconfidence into a price formation model to enable the development of more realistic forecasts of return continuation and reversal patterns. They used a dynamic overconfident model – timeline and impulse response function. Their results show that investors' perceived precision varies over time based on the presence of public signals, which is consistent with the AMH, which supports changes over time. The updating rule is that when the appearance of the next public signal pushes the accumulated public signal (and market price) toward the investor's private signal, the investor will become more confident in his or her private signal. The result is a hump-shaped impulse response function. This pattern includes a short lag momentum and a long lag reversal. The upward slope of the overreaction period suggests that positive returns tend to be followed by positive returns. The downward slope of the correction period shows that negative returns tend to follow negative returns (Daniel & Hirshleifer, 2015).

Ataullah, Vivian, and Xu (2018) examined the impact of managerial overconfidence on the debt maturity of British firms. The study analysed 192 companies, yielding 865 yearly observations from 2000 to 2010. They based their argument on the hypothesis that managerial overconfidence can alleviate the problem of underinvestment, which is often a major concern for long-term debt investors. In this context, they hypothesise that managers' overconfidence would increase the debt maturity. The researchers applied time-varying measures of overconfidence derived from analysis of computational linguistics and executives' trades in their own companies' stocks. The study results show that changes in first-person singular pronouns and optimistic tone have a positive relationship with changes in debt maturity. Overall, their study provides the first evidence of a positive relationship between overconfidence and debt maturity through overconfidence reducing the agency costs of long-term debt, consistent with the AMH hypothesis.

Risk behaviours can be erratic and change monthly (Lippi, Barbieri, Piva, & De Bondt, 2018). Lippi et al. (2018) studied 62 clients of a private bank in Northern Italy who are active traders and manage the value at risk (VaR) of part of their asset portfolios. They are also independent investors, meaning they trade without any input from a financial advisor. Through applying VaR statistics, they found that subjects generally became more risk-averse after experiencing losses and more risk-seeking after receiving gains. Monthly gains and losses that change investors' risk behaviour represent real changes in wealth but are only "on paper" and not immediately realised.

3.3.2 Investor overconfidence and stock return volatility studies

Chuang and Lee (2006) study whether trading by overconfident investors contributes to excessive volatility. They used aggregated data from all companies trading on the AMEX and NYSE from January 1963 to December 2001. They began by decomposing trading volume into two components: a trading volume component unrelated to investor overconfidence and a trading volume component related to investor overconfidence. The two components of trading volume are then incorporated into the conditional variance equation of the EGARCH model. Chuang and Lee (2006) find that the results indicate that trading volume caused by investor overconfidence adds to the observed conditional volatility. Empirically, overconfident trading exhibits a positive and significant relationship with volatility. Sheikh and Riaz (2012) study whether market gains (losses) are followed by high (low) trading activity and whether trading volume due to overconfidence leads to excessive volatility. The study analysed data from companies listed on the Karachi Stock Exchange from November 1999 to October 2010. Following the model of Chuang and Lee (2006), they found that the EGARCH model estimates indicate that the trading volume generated by investor overconfidence has a positive relationship with volatility. However, this relationship is not significant. Therefore, Sheikh and Riaz (2012) conclude that no significant evidence exists that trades associated with investor overconfidence led to increased volatility. These results are inconsistent with those of Chuang and Lee (2006), to which the investor overconfidence significantly increases market volatility.

Abbes (2013) examines whether the high levels of volatility recorded during the 2008 financial crisis were due to investor overconfidence by analysing market indices of 15 countries from January 1999 to December 2009. The study uses Chuang and Lee's (2006) model and reveals that, for the entire sample, trading volume generated by investor overconfidence was positively related to conditional volatility. Strong investor overconfidence has been observed in the stock markets of the developed countries. This suggests that investor overconfidence was a key factor in the financial instability that erupted during the 2008 global financial crisis. However, Abbes (2013) reports that there is no significant relationship between investor overconfidence bias and volatility during times of crisis, as investors lose confidence in the financial markets.

Jlassia, Naouib, and Mansour (2014) examine the impact of overconfident behaviour on dynamic volatility in global financial markets. Using daily data from 27 countries from 2000 to 2012, they found that investor overconfidence is more evident in developed than emerging markets. Except for some Asian and Latin American markets, investor overconfidence is present in both bull and bear markets. Evidence suggests that investor overconfidence was the main driving force causing and prolonging the global financial crisis in the US market and other continents. They analysed the impact of investor overconfidence on dynamic market volatility in the 27 countries divided into four subgroups: Advanced markets in Latin America, Asia, Europe, and Middle East Africa. Using a daily data set from 5 January 2000 to 12 December 2012, they provide strong empirical evidence for different levels of overconfidence in financial markets worldwide, except for Chile. This observation shows that investors only think in the short term, and the strength of their psychology often influences decisions. Therefore, the investor overconfidence bias can explain much of global financial markets' excessive and asymmetric volatility. The latter is a dynamic factor that drives strong and asymmetric trading volumes and increases stock price volatility, especially during the 2007 to 2009 global financial crisis.

Furthermore, the experimental design shows that under different market conditions, the investor overconfidence bias is the driving force behind market disruptions. The study also revealed that consistent with theoretical hypotheses, investor overconfidence is more evident in bull markets and before the crisis. These results imply that under tranquil market conditions, investors tend to ignore market warning signals and trade excessively, thereby causing an increase in asymmetric stock market volatility, contrary to the study by Abbes (2013).

Mushinada and Veluri (2018) empirically examined the impact of investor overconfidence trading on stock market volatility on the Bombay Stock Exchange (BSE). They analysed 1,290 stocks traded on the BSE between April 2004 and March 2012. The study applied the bivariate vector autoregression model, impulse response functions and EGARCH model to understand whether there is self-attribution bias and overconfident behaviour among investors. The research shows empirical evidence supporting the investor overconfidence hypothesis. The results show that overconfident investors overreact to private and public information. Based on EGARCH specifications, it was found that excessive trading by overconfident investors contributed to high stock market volatility between April 2004 and September 2008. The analysis of the relationship between return volatility and trading volume shows that excessive trading by overconfident investors contributes to the observed excess volatility. However, in the post-crisis period, from October 2008 to March 2012, Mushinada and Veluri (2018) found that market volatility was less affected by excessive trading from overconfident investors. These results contrast sharply with those of Jlassi, Naouib, and Mansour (2014), who claim that overconfident trading has a significant positive impact on stock market volatility after the global financial crisis of the year 2008.

3.3.3 Investor overconfidence and market condition studies

If investor overconfidence and trading volume are related, does this relationship change over time and market conditions? Specifically, investors in bull markets and bear markets may behave differently under the influence of investor overconfidence. Chuang and Susmel (2011) assess whether investor overconfidence was more pronounced among institutional or individual investors in the Taiwan Stock Exchange. The study analysed the weekly stock returns, turnover, and market capitalisation of all stocks listed on the Taiwan Stock Exchange from January 1996 to December 2005. Chuang and Susmel (2011) use a seemingly unrelated regression (SUR) model to examine the interaction between market returns and portfolio volume to achieve their objective. The multivariate SUR regression model shows that after positive market returns, individual investors trade more frequently in bullish markets than in non-bullish markets, supporting the AMH. However, after the market gains, the trading behaviour of institutional investors showed no significant difference between bull and bearish markets. Given that most stocks generate positive returns in bull markets, Chuang and Susmel (2011) argue that investor overconfidence is more pronounced in bull markets than in bear markets, where the level of investor overconfidence tends to decrease.

Metwally and Darwish (2015) examined the presence of investor overconfidence in the Egyptian Stock Exchange. The study sample included all stocks listed on the Egyptian Stock Exchange. However, the investor overconfidence bias was studied at the aggregate market level by examining the association between market turnover and its returns from 2002 to 2012. The sample period is divided into two periods of tranquil upward trends (2002 to 2004 and 2005 to 2007) and two periods of volatile downward trends (2008 to 2010 and 2011 to 2012). Applying the model previously used by Statman, Thorley, and Vorkink (2006), the relationship between market turnover and market returns is studied using the VAR model and its associated impulse response functions. Over the entire sample period, the regression VAR model indicates that first-lagged market returns have a significant positive relationship with current market turnover and thus coincide with the overconfidence hypothesis. These results are supported by the impulse response functions associated with the estimated VAR models. Additionally, Granger causality tests support the view that market returns Granger causes market turnover. Regarding the subsamples, Metwally and Darwish (2015) found that trading activity in the Egyptian stock market is strongly influenced by market conditions, as stated by the AMH. Specifically, the study reports that investor overconfidence triggered trading activity when the Egyptian stock market was upward.

Bao and Li (2020) examined the impact of investor overconfidence in six Asia-Pacific REIT markets, namely Australia, Hong Kong, Japan, Singapore, South Korea, and Taiwan, from the year 1994 to 2015. A vector autoregression (VAR) model was used to explore the return revenue dynamics and impulse response functions to track the effects of previous return shocks on market turnover. A significant and positive investor overconfidence effect was identified regarding the market turnover of the REIT markets in Japan, Singapore, South Korea, and Taiwan. This effect is especially strong in less efficient markets characterised by short-selling restrictions and low market transparency (for example, South Korea and Taiwan). By re-estimating the VAR model with separate bull and bear market subsamples, they found a stronger investor overconfidence effect in the bull markets for the Japanese, South Korea, and Singapore REIT markets. The research shows that the investor overconfidence effect is more evident during market booms and in inefficient market conditions. This conclusion is consistent with the AMH paradigm, which supports changes due to changing market conditions. Additionally, simulation analysis demonstrates that the investor overconfidence bias could lead to large volumes of excessive trading activity in some markets.

Mushinada (2020) argues that when market conditions change, investors become irrational, but they adapt to changing market situations and gradually reach equilibrium. However, Namouri, Jawadi, Ftiti, and Hachicha (2018) conclude that the dynamics of stock returns create curvilinear effects and vary over time. Additionally, investor confidence has a significant impact on stock returns. That is, the result of investor confidence in stock returns changes as market conditions change.

A more recent study by Kumar and Prince (2022) investigated attempts to detect investor overconfidence bias in different market scenarios in India, that is, during the pre-crash period (2006-2008), the crisis period (2008-2010) and the post-crash period (2010-2015, 2015-2020, 2020-2021). The econometric techniques used to analyse the data included Vector Autoregression (VAR), Impulse Response Function (IRF), Granger Causality test and the VAR/Block Exogeneity Wald Test. The research found that the investors were overconfident in the pre-crisis period, before the global stock market crash of 2008 and from 2015 to March 2020. In the post-crisis period, that is, in 2008-2010, 2010-2015 and 2020-2021, investors are not overconfident.

3.4 Gap in the empirical literature

The literature reviewed above outlines the gaps in the subject under consideration, which shows that while the empirical investigations of investor overconfidence under the AMH are limited, they are particularly rare in the African stock markets. The literature indicates that examining investor overconfidence over time-varying conditions is new and that the investigation is limited to a few markets. This shows that many markets still need attention when examining investor overconfidence within the AMH framework.

It can also be noted that virtually any research on the impact of market conditions on investor overconfidence in markets other than the United States, Europe, and some parts of Asia is almost lacking, which creates a need for further studies into the developing markets. The identified gaps suggest that further research on the AMH in smaller markets could shed more light on the subject matter. An attempt in this direction would contribute significantly to the existing knowledge of the AMH and bridge the gaps in the empirical literature between developed and African markets.

3.5 Summary

This chapter presented an overview of empirical studies on investor overconfidence, both in absolute form and according to the AMH. From this analysis, it can be seen that assessing the role and impact of investor overconfidence in the stock markets is controversial in the literature. Several empirical studies have been conducted to test the presence of investor overconfidence in developed and developing stock markets. Many researchers have attempted to develop theoretical models based on the investor overconfidence hypothesis to account for observed market anomalies. Studies have shown that investor overconfidence affects both institutional and individual investors. However, after the market gains, the trading behaviour of institutional investors did not show a significant difference between the bull and bear markets.

There is now a shift from an absolute framework to frameworks that change over time (time-varying frameworks). Recent evidence suggests that the AMH may be a more suitable approach and that current market efficiencies or anomalies are related to market conditions, yet there has been very little research on them. Therefore, further research is needed. Hence, this study appears to fill this gap by examining the relationship between investor overconfidence bias and stock market returns in several African stock markets, considering changes according to time and market conditions.

CHAPTER 4: RESEARCH METHODOLOGY AND DATA

4.1 Introduction

The importance of an appropriate methodology cannot be overemphasised as it is essential to achieve the study's objectives successfully. Research methodology is the process used to gather the necessary information or data to ensure that the problem and objectives of the research are effectively addressed (Bhattacharyya, 2010). It explains how the research was conducted; it is an explanation of how the research must be conducted. It provides detailed information about the methods used to collect data, why they were chosen, and how the data were collected and analysed. This chapter describes the methodology used in the study. The study examined the objectives using a quantitative approach with secondary data. This makes the study fall under the positivist paradigm. It uses secondary time series data collected over a long period and analysed using different estimation methods. This research is both empirical and quantitative and involves examining the behaviour of overconfident investors, stock market returns, and the influence of time and market conditions on the behaviour of overconfident investors. This chapter describes the data sources, collection methods, research population, sampling procedures, and statistical methods for analysis.

4.2 Population, Sampling and Data

Africa has enormous economic potential but is hampered by unstable political regimes, weak public institutions, and poor policy measures. However, recent years have seen significant progress in these areas, opening up positive prospects for the continent. The stock market landscape in Africa has evolved rapidly over the past two decades (African Securities Exchange Association (ASEA), (2022). Although African capital markets still lack adequate quantitative research, the highly diverse capital market and stock exchange landscape continues to evolve (Schiereck, Freytag, Grimm, & Bretschneider, 2018). African stock markets have grown in size and number, increasing opportunities for local institutional and retail investors to support economic development. The African continent has 35 organised stock exchanges where securities can be listed (Appendix 1). These exchanges represent the capital markets of 40 African countries, representing approximately 72% of African sovereign states. Today, Africa consists of 55 countries fully recognised by the African Union (AU), representing all countries on the African continent, all of which are members of the AU (African Union, 2022). The aggregate market capitalisation of stock exchanges in the African region has increased in tandem, from USD 260 billion in 2000 to USD 738 billion in 2011 and to USD 1.6 trillion in 2021 (ASEA, 2022).

Some of these markets are over a hundred years old (for example, the Egyptian Stock Exchange, founded in 1883, and the Johannesburg Stock Exchange, founded in 1887) and offer investors and businesses the ability to access equity capital, bond markets, stock trading, or derivative products. Thanks to modern regulators, they allow financial transactions to be carried out through well-established trading platforms and ensure efficiency and security. Other markets are still young, only list a small number of securities, and consider dozens of weekly transactions as peak trading activity (Schiereck et al., 2018). The two oldest stock exchanges in Africa are the Egyptian Stock Exchange and the Johannesburg Stock Exchange (JSE). The Alexandria Stock Exchange in Egypt opened in 1883 and today forms the Egyptian Stock Exchange (along with the Cairo Stock Exchange, established in 1903). The JSE opened its doors in 1887. The youngest exchanges are the ALTX East African Exchange in Uganda, the Maseru Stock Exchange in Lesotho, and ZAR X in South Africa. The trio officially started operations in 2016 (Schiereck et al., 2018) and, most recently, the Victoria Falls Exchange (VFEX), which commenced operations in 2020. The Johannesburg Stock Exchange is the leading financial exchange in Africa and one of the 20 largest exchanges in the world by market capitalisation, with a 135-year-old history. As of July 2022, its market capitalisation stood at USD 1.2 trillion (ASEA, 2022). The JSE has shown resilient performance in recent years despite a significant decline in net listed shares. The year 2021 was marked by 25 delistings, compared with 20 in 2020, although these were mainly due to mergers and acquisitions (M&A) transactions and deals at small and medium-sized counters. However, the total market capitalisation of all JSE entities continues to increase (ASEA, 2022).

Because the nature of the study requires a fairly long sample of data to examine the changing behaviour of stock market returns over time, the availability of an averagely long sample size was the basis for market selection. As a result, relatively new markets such as Angola, Lesotho, Libya, Sierra Leone, Seychelles, Somalia, Uganda, Victoria Falls and ZAR X were automatically eliminated. The same applies to markets that lack long and consistent data. Data from some countries were missing, which was corrected by excluding these countries from the model, reducing the sample size. Excluding countries with insufficient data has been widely accepted in the literature (Basiewicz & Auret, 2010; Upreti, 2015). All the African stock markets were considered, but a final sample of seven markets was selected based on the available data. The selected markets are the Casablanca Stock Exchange (CSE), the Egyptian Exchange (EGX), the Johannesburg Stock Exchange (JSE), the Nigerian Stock Exchange (NGX), the Nairobi Securities Exchange (NSE), Ghana Stock Exchange (GSE) and the Stock Exchange of Mauritius (SEM). To be included in the sample, a market had to be a member of the African Securities Exchanges Association (ASEA), a leading securities association in Africa, established in 1993 in Nairobi, with the Nairobi Securities Exchange as a founding member. It aims to develop member exchanges, promote capital market activities, and provide a network platform. As of 2022, ASEA has 28 full members serving 38 countries. More than 2,400 companies are listed on the member network's stock markets, with a total market capitalisation of approximately USD 2 trillion (ASEA, 2022).

Regarding market capitalisation, the selected markets account for approximately 70% of the continent's total market capitalisation. As of July 2022, the market capitalisation for the selected stock markets was as follows: the CSE - USD 62.9 billion; the EGX - USD 34.9 billion; the JSE - USD 1.2 trillion; the NGX - USD 68.9 billion, the NSE - USD 16.9 billion, the GSE - USD 7.5 billion and the SEM - USD 7.8 billion in terms of market capitalisation according to the ASEA (2022) report. These figures confirm that the selected sample covered sufficient market capitalisation. The selected sample includes large, medium, and small stock markets. Morocco, Nigeria, and South Africa are the continent's largest markets, while Egypt and Kenya are middle markets. The presence of Ghana and Mauritius ensures that smaller markets are also represented. The study was selected based on data availability and covers 15 years, starting in January 2005 and ending in December 2019, except for the GSE and the NSE. The GSE and NSE samples spanned 2011:01 to 2019:12 and 2008:02 to 2019:12, respectively, because that was when the broad market indices were introduced. The period is also long enough to capture several changes in market conditions for data analysis, from before the global financial crisis to after the crisis. The study uses expansion and contraction phases as indicators for bull and bear markets, respectively. When looking at trends, the sample is classified into normal, bullish, and bearish categories (Klein & Rosenfeld, 1987). At least two consecutive significant changes must exist for each category. Assuming a significant rise in the market index for one period with average bordering periods, that is categorised as average. Thus, if the index is increasing or normalising in one period, bordering bearish periods, this is classified as bearish.

Following the methodology of Metwally and Darwish (2015), Gupta et al. (2018), and Kumar and Prince (2022), the entire period was divided into five sub-periods depicting different market states. The studies by Obalade, Nhlapo and Muzindutsi (2022) and Obalade et al., (2022) also used different periods to test AMH. The literature suggests that different market states can change trading activity and thus make investors overconfident. Market conditions affect investor's emotions. Unexpected and sudden changes in the market can cause investors to adjust their beliefs and change their views. These sudden market changes included the United States subprime mortgage crisis and the stock market crash of 2007- 2010, which triggered the 2007–2008 global economic crisis. Subsequently, the European sovereign debt crisis of 2008–2012 and the Arab Revolution of 2010–2011, as such, the entire sample period is divided into five sub-periods to indicate the different market states in the pre-crash period, the crash period, and the post-crash period. The divisions were done using the diagrams below (Figures 4.1 and 4.2). Three sub-periods represent tranquil upward-trending samples (2005-2007), (2014-2016) and (2017-2019), and the remaining two periods are volatile and downward-trending samples (2008-2010) and (2011-2013). The sub-periods were used to compare investor overconfidence under the different market conditions, representing market states 1 to 5.

The sub-periods are:

Tranquil periods	Volatile periods
Sub period 1: 2005 – 2007	Sub period 2: 2008 – 2010
Sub period 4: 2014 – 2016	Sub period 3: 2011 – 2013
Sub period 5: 2017 – 2019	

Source: Author (2023)

The tests were performed at the market level by examining the relationship between market returns and market turnover under different market conditions, aiming to confirm or refute the idea that investor overconfidence behaviour is static, varying, or adaptive. For each objective, the proposed models and equations are estimated for each stock market, and the results are compared across the selected stock markets. Previous studies highlight that changes in investor overconfidence are observed over weekly, monthly, and yearly periods (Statman, Thorley, & Vorkink, 2006; Metwally & Darwish, 2015). Hence, this study focused on the weekly horizon because relatively high-frequency data can yield better results and cover the full economic cycles. The weekly data was used due to the small market size, thin trading, and to avoid the day-of-the-week effect (Darwish, 2012). Secondary data was obtained from Bloomberg, a leading global financial data provider. The data sample used in this study includes weekly price indices and trading volume. Standardised returns and the trading volumes for each of the broad market indexes, specifically the Morocco/Casablanca MASI Free Float All Share Index (MOSENEW), the Egyptian Exchange Benchmark Index (EGX 30), the Johannesburg Stock Exchange All Share Index (JALSH), the Nigerian Stock Exchange All Share Index (NGXINDX), the Nairobi Securities Exchange All-Share Index (NSEASI), the Ghana Stock Exchange Composite Index (GSE-CI) and the Stock Exchange of Mauritius All Share Index (SEMDEX) were obtained from Bloomberg and calculated according to the following formula:

$$R_t = Log\left(\frac{P_t}{P_{t-1}}\right) \tag{5}$$

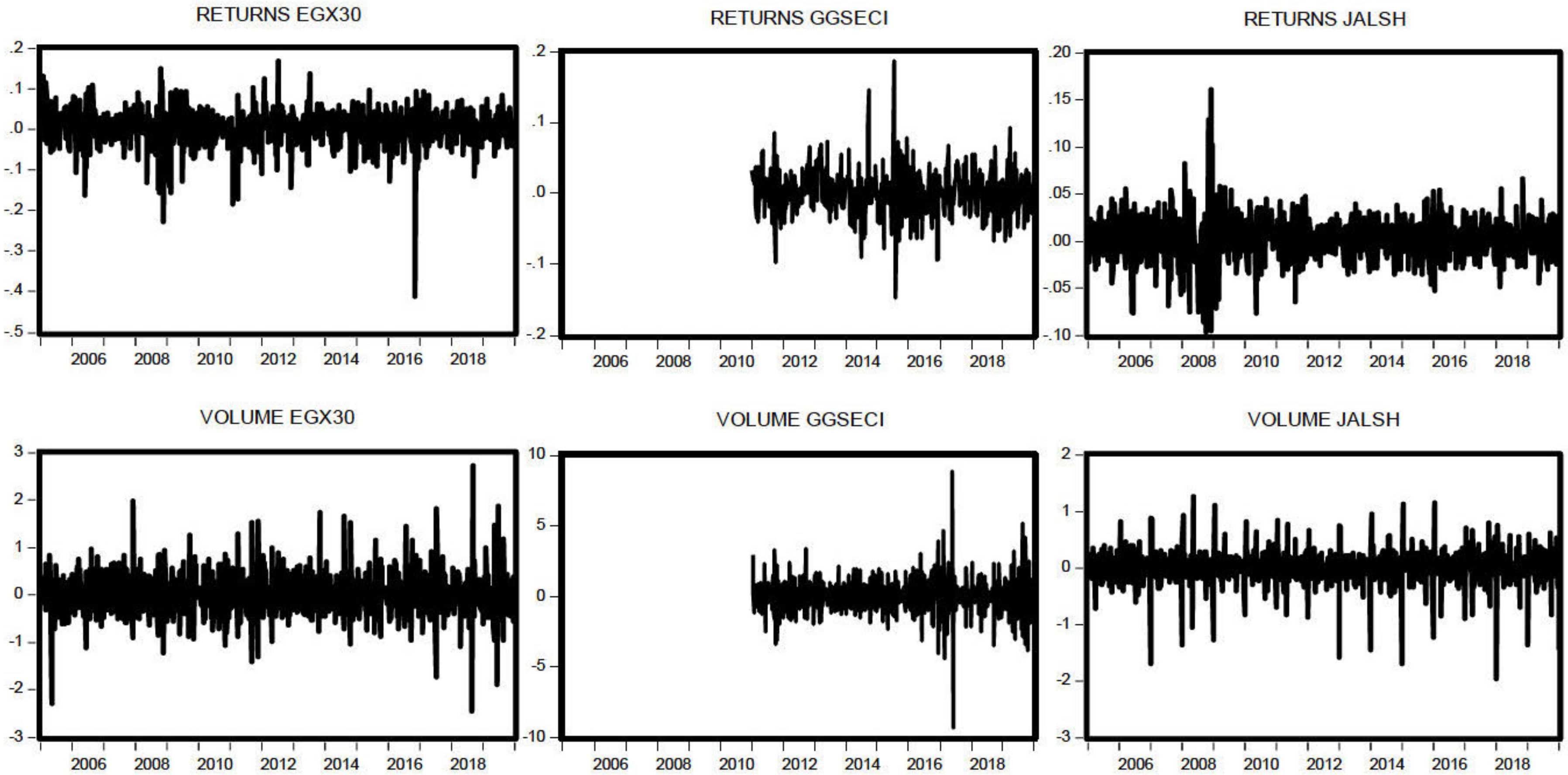
Where R_t represents stock index return at time t. P_t is the closing index price in week t, and P_{t-1} represents price index at t-1, respectively.

The Casablanca Stock Exchange is one of the largest exchanges in Africa, with a market capitalisation of US$ 62.9 billion. It is one of Africa's most developed stock exchanges, following reforms and technological advances made since the 2000s and the implementation of the Millenium IT trading and surveillance platform in 2016 (ASEA, 2022). The priority in Morocco's new development model is to restore its stock market and strengthen its role in financing economic growth and moving towards emerging market status. The broad market index of the Casablanca Stock Exchange is the Moroccan All Shares Index (MASI) Free Float All Share Index (MOSENEW), first published on January 1, 2002. It is an index that broadly tracks all securities listed on a stock exchange. In 2004, the Casablanca Stock Exchange revised the method of calculating its indices based on the floating concept to suit better the company's stock market position and its position in the index. Since then, the index has been commonly known as the MASI Float or the MASI Free Float Index.

The Egyptian Exchange's EGX 30 Index is a free float capitalisation-weighted index of the 30 largest capitalised and most liquid stocks traded on the Egyptian Stock Exchange. The index was developed with a base level of 1,000 on 1 January 1998 and was formerly known as the CASE 30 Index (Bloomberg). The Johannesburg Stock Exchange All Share Index (JALSH), also known as the FTSE/JSE All Share Index, covers 99% of the total market capitalisation (before applying any investment weighting) of all common stocks listed on the main board of the JSE, subject to minimum free float and liquidity criteria.

The Nigerian Stock Exchange has seen healthy growth recently, with market capitalisation increasing by 62% and 6% in 2020 and 2021, respectively. Equity turnover has slowed significantly after the extreme highs recorded during the COVID-19 pandemic. As of July 2022, NGX's total market capitalisation stood at US$ 68.9 billion (ASEA, 2022). The broad market index is the Nigerian Stock Exchange All Share Index (NGXINDX). The All Share Index tracks the overall market performance of all stocks listed on the Nigerian Stock Exchange, including those listed on the Growth Board, regardless of their capitalisation. The Nairobi Securities Exchange has a total market capitalisation of approximately US$ 16.9 billion as of mid-2022, an increase of more than 11% over the previous year (ASEA, 2022). Its broad market index is the Nairobi Stock Exchange All Share Index (NSEASI). It was introduced as an alternative index in 2008, with a base value of 100 in January 2008. It is a market capitalisation-weighted index that includes all stocks on the NSE. Its measurement and attention are therefore focused on total market capitalisation rather than on the price movements of certain counters. Prices are based on the latest trading information from the NSE automated trading system.

The Ghana Stock Exchange rebounded strongly in 2021, with total market capitalisation increasing by 19% to US$ 7.8 billion. This development is explained by a 43% increase in domestic companies' market capitalisation, reflected in domestic investors' participation from 16% to 32% (ASEA, 2022). However, foreign investors continue to dominate the market, accounting for 68% of the transaction value. By mid-2022, the GSE's market capitalisation had fallen to US$ 7.5 billion (ASEA, 2022). Its broad market index is the Ghana Stock Exchange Composite Index (GSE-CI). This market capitalisation-weighted index includes all listed common stocks, excluding shares of listed companies whose shares are listed on other markets. This is a capitalization-weighted index with a base value of 1000 as of 31 December 2010. The index calculation is based on an average closing price weighted by the volume of stocks that comprise the index. The Stock Exchange of Mauritius has a market capitalisation of US$ 7.8 billion as of mid-2022. Its listing pipeline is robust, with 120 recorded between 2014 and 2019 (ASEA, 2022). SEM's broad market index is the Mauritius Stock Exchange All Share Index (SEMDEX). This is the main stock index that tracks the performance of all publicly traded companies. This is a capitalisation-weighted floating index, launched when SEM was launched on July 5, 1989, with an index value of 100. The SEMDEX is considered an all-share index designed to capture price movements of all common stocks listed on the official market and meets SEM's free float requirements as defined in the official market's listing rules.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VOLUME GGSECI
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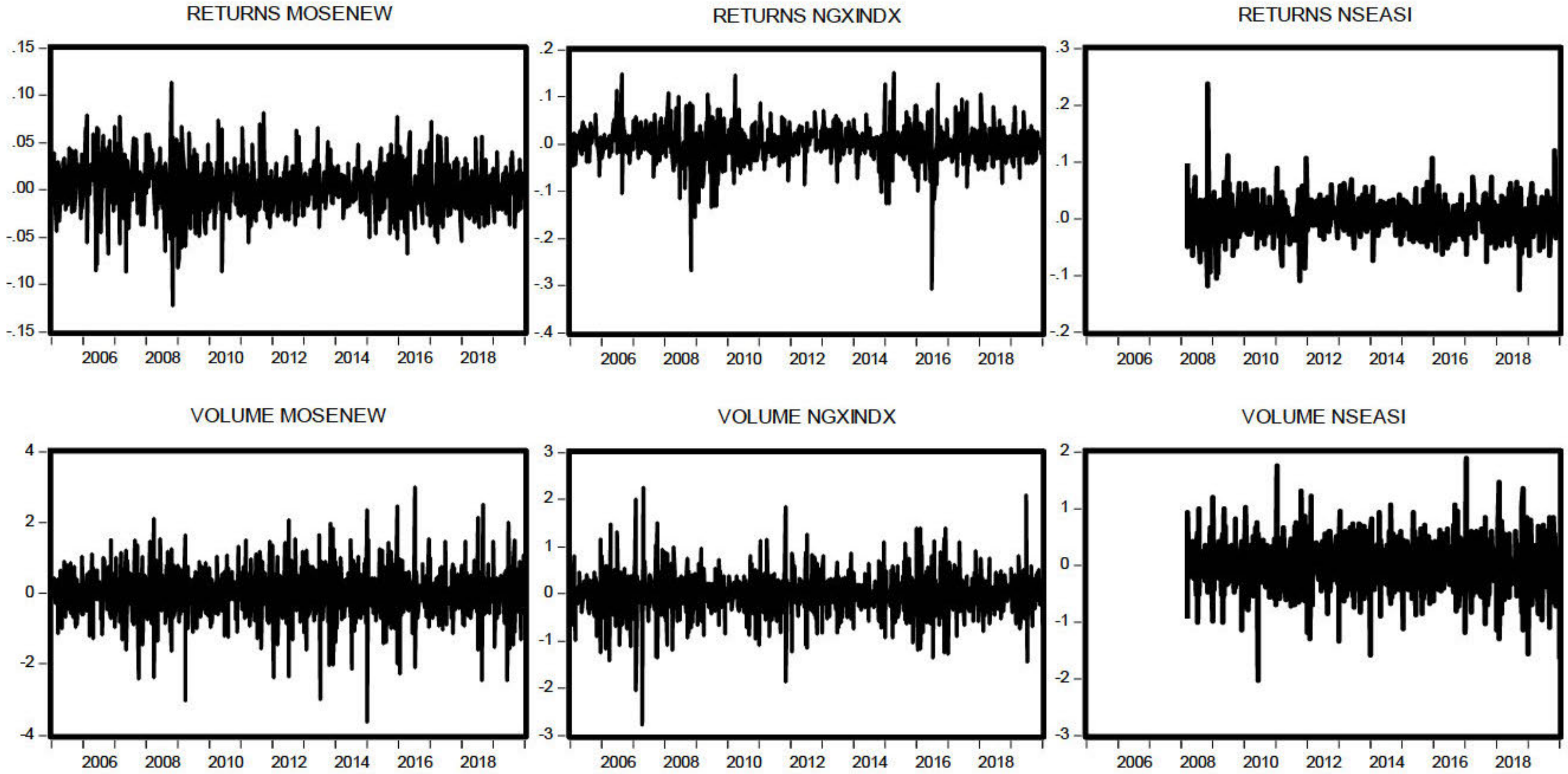
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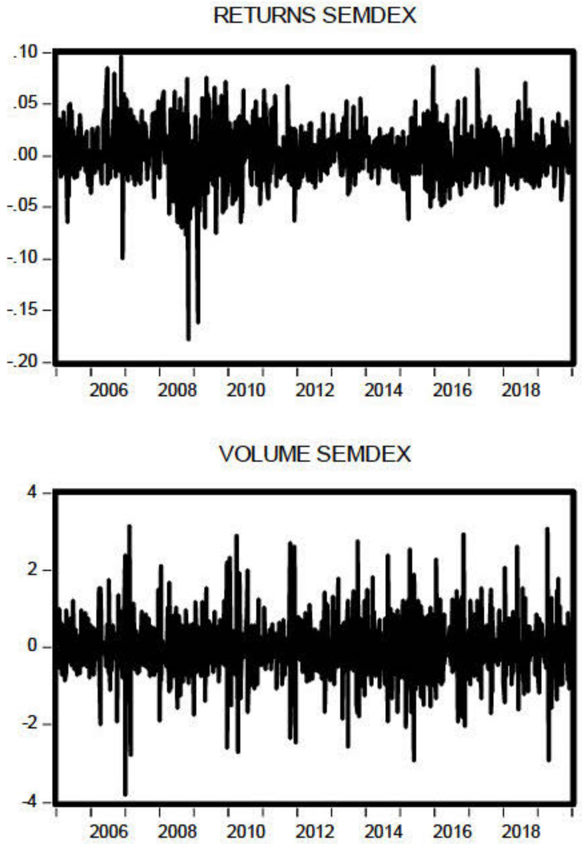

Figure 1.1 Graphs to choose the sub periods interval

Source: Author (2023)

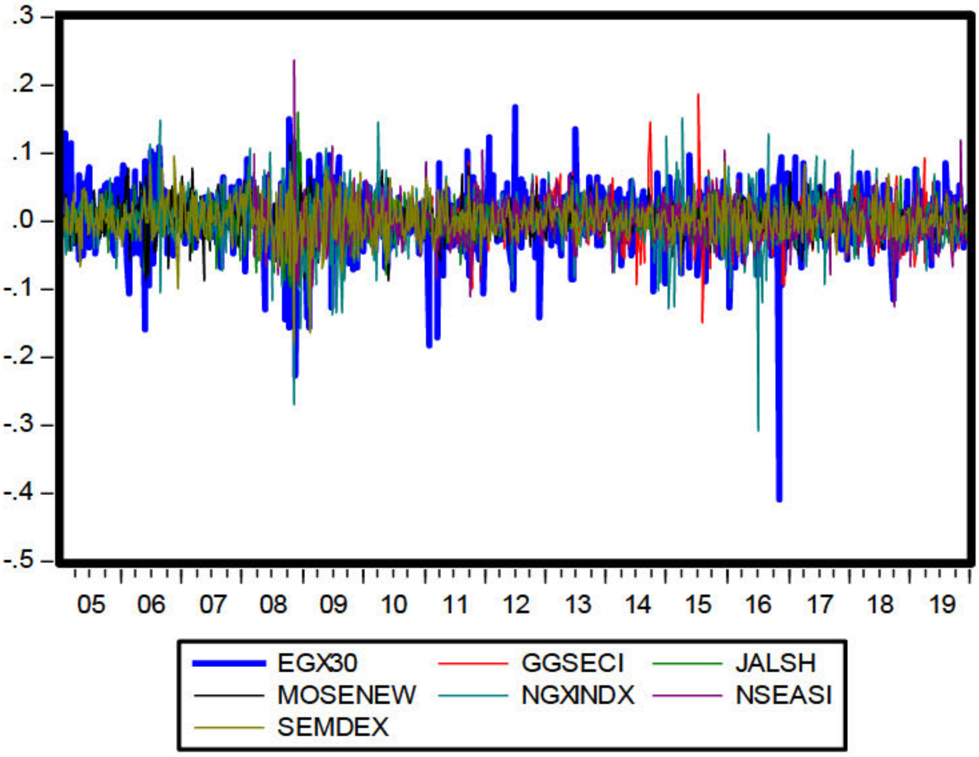

Figure 4.2 Graph showing combined markets

Author (2023)

4.3 Preliminary and Diagnostic Tests

Before modelling the relationship, that is, running models of investor overconfidence, diagnostic and preliminary tests were performed on the time series data to understand the characteristics and their significance for research modelling. These consist of tests for stationarity. If the structure of a time series remains consistent over time, that is, when the series evolves around its mean with constant variance, it is said to follow a stationary process. To determine whether a unit root exists, the study used various unit root testing models developed by Dickey and Fuller (ADF, 1979; 1981), Kwiatkowski, Phillips, Schmidt, and Shin (KPSS, 1992). To apply Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models, the study first performed an Autoregressive Conditional Heteroskedasticity (ARCH) effect test to determine whether or not conditional heteroskedasticity exists. If all the series are non-stationary at a certain level, the initial difference would be stationary at the same level of lags. The Akaike Information Criterion (AIC) and Schwartz Bayesian Criterion (SBIC) were applied for the appropriate lag length.

4.3.1 Normality test

A statistical test called Jarque-Bera (JB) was used to determine whether the series of returns followed a normal distribution. The deviation of a series from normality is tested using a goodness-of-fit test based on the skewness and kurtosis of the data (Jarque & Bera, 1980; 1987). The JB statistic compares the skewness S and kurtosis K of series with normal distributions to determine their variance. Theoretically, S and K have values of 0 and 3, respectively, under normal conditions.

The Jarque-Bera test hypothesis is written as:

H_0: Normal distribution

H_1: Non-normal distribution

The JB test follows a Chi-squared distribution with two degrees of freedom when the normally distributed series represents the null hypothesis. Whether or not the null hypothesis is rejected depends on the probability value (p-value) connected to the JB test statistic. Therefore, when the specified significance level is greater than the corresponding probability value, the null hypothesis of a normal distribution is rejected.

Therefore, we must reject H_0 at level α

if $\mathrm{JB} \geq \mathrm{X}_1{}^2 - \alpha, 2$

The test statistic JB of Jarque-Bera is defined by

$$JB = \frac{\eta}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \tag{6}$$

η represents the number of coefficients used to generate the series, while S and K represent the skewness and the kurtosis values of the series, respectively.

Where the sample skewness, S is given by:

$$S = \frac{1}{N}\sum_{i=1}^{N} \frac{(y_i - \check{y})^3}{\check{\delta}} \tag{7}$$

Where y is the random observation in the series, $\check{y}$ is the mean value of the series, N is the total number of observations in the series, and $\check{\delta}$ is the sample standard deviation estimator based on the biased approximation of the variance, also known as the variance-based standard deviation estimator. Skewness evaluates the asymmetric distribution of a sequence (Kim & White, 2004). This information reveals which side of the distribution has a longer tail. If the series is symmetric or evenly distributed, then the skewness is 0. A positive distribution skewness indicates a long right tail, while a negative skewness indicates a long left tail.

The standard deviation estimator $\check{\delta}$ based on the variance is given by:

$$\check{\delta} = \delta\sqrt{\frac{(N-1)}{N}} \tag{8}$$

Where standard deviation, δ is

$$\delta = \sqrt{\frac{\sum(y_i - \check{y})^2}{N-1}} \tag{9}$$

The sample kurtosis K is given by:

$$K = \frac{1}{N}\sum_{i=1}^{N}\frac{(y_i - \check{y})^4}{\check{\delta}} \tag{10}$$

Where $\check{\delta}$ is also based on a biased variance estimator, while y, $\check{y}$ and N follow the definition in (6) above. The kurtosis of a serial distribution indicates whether it is peaky or flat (Ruppert, 1987). The kurtosis value is three if a normal distribution applies to the series. The distribution is said to be peaked (leptokurtic) or flat (platykurtic) if the kurtosis is greater or less than three, respectively.

4.3.2 Unit Root and Stationarity Tests

Checking whether the time series used in the model is stationary was the first step in dealing with spurious correlations. Evidence shows that most of the time series data on economic indicators are non-stationary. The problem is that the estimation produces erroneous results if the model is used to estimate non-stationary data series (Gujarati, Porter & Pal, 2020). When a time series deviates from the mean with constant variance, it is said to follow a stationary process if its structure does not change over time. If the expected value and variance are constant over time and the covariance depends only on the difference between two time periods and not on the time periods themselves, then the time series is considered stationary (Wooldridge, 2006). The sequence can be considered stationary if these three conditions are met. The most common unit root test used in this research is the Augmented Dick-Fuller (ADF) test, which determines whether a unit root exists or not.

4.3.2.1 Augmented Dick-Fuller (ADF) test.

Because the series has a unit root, it cannot be said to be stationary, which is the null hypothesis. The differences can be used to convert the time series to a stationary series if the model time series cannot reject the null hypothesis of the ADF test. Differentiating the time series results in losing significant information, reducing the scope of economic interpretation. Checking whether the variables in the model are co-integrated can provide a solution to this conundrum. The following Augmented Dick-Fuller (ADF) test was applied:

$$\Delta Y_t = \alpha_0 + \beta Y_{t-1} + \sum_{j=1}^{k} \Phi_j \Delta Y_{t-j} + \varepsilon_t \tag{11}$$

$$\Delta Y_t = \alpha_0 + Y_t + \beta Y_{t-1} + \sum_{j=1}^{k} \Phi_j \Delta Y_{t-j} + \varepsilon_t \tag{12}$$

The unit root testing theory underlies testing for “harmful” serial correlation. For the null hypothesis ADF, Y = 0, and the alternative hypothesis is Y ≠ 0. Rejecting the null hypothesis means the series is stationary and no unit root exists. Equation (11) tests for a zero-unit root against the stationary trend alternative in Y_t where in Y_t refers to the time series being studied. The term ΔY_{t-j} is the first difference lagged to account for serial correlation in the errors. The ADF has been criticised for its low power if the process is stationary and thus tends to under-reject the null hypothesis of a unit root (Brooks, 2019; Gujarati, Porter & Pal, 2020). The test is susceptible to size distortion, which increases the likelihood of making a Type I error, rejecting the null hypothesis when it is true (Gujarati, Porter & Pal, 2020). To overcome the limitations of ADF testing, Brooks (2019) proposed combining stationarity testing and unit roots tests, a method known as confirmatory data analysis. Therefore, the ADF test results are at odds with the alternative test results, specifically the KPSS. The KPSS has been added as a verification test.

4.3.2.2 Kwiatkowski, Phillips, Schmidt, and Shin (KPSS)

The Kwiatkowski-Phillips-Schmidt-Shin test, abbreviated KPSS, is a form of unit root test that tests the stationarity of a certain series around a deterministic trend. The test shares certain principles with the ADF test. Contrary to popular belief, it cannot be used in place of the ADF test. This can lead to misunderstandings about stationarity, which can easily be overlooked and cause more problems in the future. The null hypothesis of the KPSS test states that the series is stationary, which is a significant difference from the ADF test. Therefore, the two ways of interpreting p-values are exactly the opposite of each other. The series is not stationary if the p-value is less than the significance level (e.g., 0.05). Meanwhile, ADF testing means the tested series is stationary (Prabhakaran, 2019).

The KPSS test is a popular stationarity test whose regression test has the following functional form:

$$sr_t = \beta^I D_t + \mu_t + \mu_t, \;\; \mu_t = \mu_{t-1} + \varepsilon_t, \;\; N(0, \sigma_e^2) \qquad (13)$$

Where D_t contains deterministic components (constant or constant plus time trend), μ_t is I (0) and can be non-uniform. μ_t is a pure random walk with innovation variance σ_e^2. The null hypothesis is formulated as H_0: $\sigma_e^2 = 0$, that is I (0), which implies that μ_t is a constant.

The KPSS statistics can be denoted as follows:

$$KPSS = \frac{(T^{-2} \sum_{t=0}^{T} S_t^2)}{\lambda^2} \qquad (14)$$

Where:

$$S_t = \sum_{j=1}^{T} \mu_j \qquad (15)$$

μ_t is the residual of a regression of sr_t on D_t and λ^2 is a consistent estimate of the long-run variance of μ_t.

This series can be co-integrated into the KPSS test if the null hypothesis of stationarity cannot be ignored. The ability of the KPSS test to assess for stationarity in the “existence of a deterministic[4] trend" significantly distinguishes it from the ADF tests. This means that even if a series increases or decreases, the test cannot definitively reject the null hypothesis (the series is stationary) (Prabhakaran, 2019). KPSS should be trusted when it conflicts with the ADF results (Pfaff, 2008).

4.3.3 Heteroscedasticity test

Engle (1982), Bollerslev (1986), Gourieroux (1992), Gourieroux and Montfort (1992), and Nelson (1991) proposed approaches to Autoregressive conditional heteroskedasticity (ARCH). The model is a normal instantaneous return distribution with mean and variance conditioned for part of the process. Autoregressive conditional heteroskedasticity models have been widely used in applied research since Engle's landmark publication in 1982. Engle also demonstrated that the presence of the ARCH effects makes the ordinary least squares (OLS) estimator incoherent. He suggested using the Lagrange multiplier (LM) test, commonly used as a diagnostic tool in regression analysis, to test for ARCH effects. A dynamic process of conditional variance can cause a time series to be uncorrelated but still serially dependent. The autoregressive conditional heteroskedasticity effect is characterised by conditional heteroskedasticity or autocorrelation in the squared series of the time series. Engle used a Lagrange multiplier test called the ARCH test Engle (1982) to evaluate the significance of the ARCH effects.

Consider a return time series.

$$r_t = \mu_t + \varepsilon_t \tag{16}$$

Where, μ_t is the conditional mean of the process, and ε_t is an innovation process with a mean of zero.

Suppose the innovations are generated as:

$$\varepsilon_t = \sigma_t z_t \tag{17}$$

Where, z_t is an independent and identically distributed process with mean 0 and, variance 1.

4. The word 'deterministic' implies that the slope of the trend in the series does not change permanently. Even if the series goes through a shock, it tends to regain its original path

Thus,

$$E(\varepsilon_t \varepsilon_{t+h}) = 0 \tag{18}$$

For all lags $h \neq 0$ and the innovations are uncorrelated.

Let H_t denote the history of the process available at time t. The conditional variance of y_t is

$$Var\left(\frac{r_t}{H_{t-1}}\right) = Var\left(\frac{\varepsilon_t}{H_{t-1}}\right) = E\left(\frac{\varepsilon_t^2}{H_{t-1}}\right) = \sigma_t^2 \tag{19}$$

Therefore, conditional heteroscedasticity in the variance process is equivalent to autocorrelation in the squared innovation process.

Define the residual series

$$\varepsilon_t = r_t - \hat{\mu}_x \tag{20}$$

The residuals are uncorrelated with mean zero if the conditional mean model fully takes into account all autocorrelation in the original series, r_t. However, the residuals may still be serially dependent.

The null hypothesis for Engle's ARCH test is,

$$H_0: \alpha_0 = \alpha_1 = \ldots = \alpha_m = 0 \tag{21}$$

The alternative hypothesis is autocorrelation in the squared residuals, given by the regression.

$$H_a: \varepsilon_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_m \varepsilon_{t-m}^2 + \mu_t \tag{22}$$

Where, μ_t is a white noise error process.

The lag m in the alternative hypothesis must be specified to perform the test using the ARCH test. The F statistic for the regression on the squared residuals serves as the test statistic. The F statistic has m degrees of freedom and follows a χ^2 distribution under the null hypothesis.

When the critical value is high, the null hypothesis is rejected in favour of the alternative hypothesis.

4.3.4 Autocorrelation Tests

The residuals' autoregressive conditional heteroscedasticity (ARCH) can be tested using the autocorrelation and partial autocorrelation of the squared residuals and the Ljung-Box Q statistics. The autocorrelations and partial autocorrelations must be zero at all lags, and the Q statistics would not be significant if there is no ARCH in the residuals. The test statistic to test the null hypothesis that there is no autocorrelation up to order. The Q statistic at the lag is calculated as follows:

$$Q_{LB} = T(T+2)\sum_{j=1}^{k}\frac{\tau_j^2}{T-J} \tag{23}$$

Where T is the number of observations and τ_j is the jth autocorrelation. Under the null hypothesis, Q is asymptotically distributed as a χ^2 with degrees of freedom equal to the number of autocorrelations if the series is not based on the outcomes of ARIMA estimation results. The appropriate degrees of freedom should be modified to reflect the number of autocorrelations minus the number of previously calculated AR and MA coefficients if the series represents the residuals of the ARIMA estimate.

4.4 Approach to achieve the study objectives

4.4.1 Objective 1: Measurement of investor overconfidence

Any study of investor overconfidence faces an important problem: finding an accurate measure or index of investor overconfidence. Among many other researchers, Baker and Wurgler (2011) argue that finding a direct measure of investor overconfidence is difficult. This challenge stems from the difficulty of accurately and directly measuring biased opinions or views (Malmendier & Tate, 2005). Therefore, the best possible way to measure investor overconfidence is to use proxies. There is currently no standardised method to determine investor overconfidence (Deaves, Luders, & Luo, 2008; Merkle & Weber, 2011; Michailova & Katter, 2014; Olsson, 2014; Parker & Stone, 2014; Langnickel & Zeisberger, 2016; Adebambo & Yen, 2017; Spiwoks & Bizer, 2018). Many tests, tasks, and measures are used, but they do not always provide a reliable indicator of investor overconfidence (as mentioned and discussed in Chapter 2). Therefore, this study aimed to quantify investors' overconfidence in the African stock markets. Based on market data, this study suggests a new investor overconfidence index. Confidence intervals, turnover, portfolio risk, and diversity level are some of the metrics mainly used in the previous studies. To quantify investor overconfidence, Deaves, Luders, and Luo (2009) and Deaves, Luders, and Schröder (2010) advise against the use of questionnaire surveys and laboratory experiments. They argue that since these tests are prone to be inaccurate, they should be used cautiously.

According to the theories put forward by Odean (1998), Shiller (2000), Chuang and Lee (2006), and Statman, Thorley and Vorkink (2006), investor overconfidence at the market level increases trading volume and stock market volatility deepens the market (Kyle & Wang, 1997; Benos, 1998; Odean, 1999), and makes returns on the financial assets predictable (Daniel, Hirshleifer, & Subrahmanyam, 1998; 2001; Scheinkman & Xiong, 2003). According to this data, investor overconfidence strongly correlates with market turnover, depth, historical market performance, and volatility. The above measures are merged into a composite score of investor overconfidence to increase power and reduce noise. Market turnover, depth, prior market performance and volatility are the four variables that make up the index. The study constructs an investor overconfidence index using a method similar to that used by Gompers, Ishii, and Metrick (2003) and Adebambo and Yan (2017). The main difference is that while previous research was based on stock fund managers' holdings and personality traits, the current study is based on market-wide data and continuous variables.

Percentile rankings were used in the study for the four variables. These percentile ranks are constructed in such a way that the higher value corresponds to higher investor overconfidence. For example, on market turnover the top 1% showing highest turnover was assigned a score of 1. In the same vein, bottom 1% showing lowest turnover was assigned a score of 0.01. A summation of the scores on the four components taken gave the investor overconfidence index. This index takes values from zero to four, with index high values showing high degree of investor overconfidence. The number 0 shows no investor overconfidence. Using this technique, it is possible to capture many aspects of the investor overconfidence. The advantage is that it is thrifty and lessens noise associated with the individual proxies (Adebambo & Yan, 2017). Seven indices (one for each of the seven markets) were constructed, and the estimates were compared to confirm whether they differed from each other.

4.4.1.1 Measuring of market turnover

The total value of shares traded during a given period is called stock market turnover. Statman, Thorley, and Vorkink (2006) specify that this period can be annual, quarterly, monthly, weekly, or daily. Shares traded divided by the number of shares outstanding and the aggregate stock turnover into market turnover on a value-weighted rather than equal basis is a metric of turnover used by Lo and Wang (2000). Value-weighted market turnover, or the dollar value of all traded stocks divided by the total dollar value of the market, is algebraically equivalent to total dollar turnover. Market turnover is calculated based on the market value proportion of each stock at time t, which is the average turnover of all common stocks traded on the market at that time.

Trading volume fluctuates based on the number of shares outstanding, although this is a natural measure of trading activity. The study used the Lo and Wang (2000) technique, dividing trading volume by the number of shares outstanding, to eliminate this confusing effect;

$$T_t = \frac{V_t}{S_t} \tag{24}$$

Where, T_t is turnover, V_t is the trading volume per period *t* and S_t is the number of outstanding shares for that particular period, and for this study, it is weekly. The average market-wide turnover is the summation of all weekly turnovers,

$$T_M = \sum_{i=1}^{N} T_i \tag{25}$$

Where N is the number of weeks in the sample period.

4.4.1.2 Measuring market depth

If a market absorbs large quantities without a significant impact on price, then it is a deep market. Information and noisy trading can cause price fluctuations. Even when some information is made public, trade does not flow from it (Kyle, 1985; Engle & Lange, 2001). The ability to buy or sell a specific amount of an asset without affecting the stated price is called depth. In other words, the relationship between order flow and price change is represented by market depth. The advertised price does not change because there is no desire to change the price when demand (buying) and supply (selling) are quantitatively equal (Olbryś & Ostrowski, 2021).

Several techniques can be used to estimate depth values. In the related literature, the following indicators of market depth are proposed:

• Different iterations of order rates are used as a measure of actual market depth (Engle & Lange, 2001; Ranaldo, 2001; von Wyss, 2004; Olbryś, 2017; Olbryś, & Mursztyn, 2017),

• Depth is calculated as the total number of units offered at the asking price and the number of units offered at the bid price (Huberman & Halka, 2001; Ranaldo, 2001; Wong & Fung, 2002; von Wyss, 2004),

• Average depth of bid and ask (Chordia, Roll, & Subrahmanyam, 2000, 2001; von Wyss, 2004),

• Dollar depth, or typical dollar depth measured in terms of money (Chordia, Roll, & Subrahmanyam, 2001; Huberman & Halka, 2001),

• A modified depth measure for the limit order book (Lin, Sun, & Tsai, 2012).

Order imbalance measures are the most frequently used (Olbryś & Ostrowski, 2021).

The revised order ratio (OR) indicator of Olbryś and Ostrowski (2021) is a revised indicator of market depth that effectively captures market order imbalance. Previous order ratio, a more accurate indicator of market depth (for example, Ranaldo, 2001; Olbryś, 2017; Olbrys & Mursztyn, 2017), contrasts daily trading volume with market depth measured by the imbalance of orders.

The revised version of Olbryś and Ostrowski's (2021) order ratio identified by:

$$OR = \frac{|CTV_b - CTV_s|}{CTV_b + CTV_s} \tag{26}$$

Where, $OR \in [0, 1]$ and the sums $CTV_b = \sum_{i=1}^{m} Vbuy_i$, $CTV_s = \sum_{j=1}^{k} Vsell_j$, represents the cumulative trading volume of transactions classified as buyer-initiated or seller-initiated, respectively. The modification is in the denominator $\sum_{n=1}^{m+k} V_n = CTV_b + CTV_s$ represents the cumulative trading volume for all classified transactions over a given period (in the frequently used version of the OR indicator, the denominator includes the cumulative trading volume for all transactions in a given period during the period under study).

Since it increases as the spread in the numerator widens, the OR indicator (equation 26) represents market imbalance. A high order rate indicates a shallow market with little liquidity. Conversely, a high order rate indicates a deep and liquid market. When the daily trading volume classified as transactions made by buyers or sellers is equal, the value of the daily order ratio is zero. Additionally, the value of the daily order rate is set to 0 in one of two cases: (1) when not all trades of the day are classified or (2) when the total daily trading volume is zero (Olbryś & Mursztyn, 2019).

The study applied an alternative solution, VNET, previously used by Engle and Lange (2001). Various summary metrics are generated for each price period. The underlying data are the number of transactions, total volume exchanged, and net price movements. The main statistic used in this study is VNET, which was first used by Engle and Lange in 2001. It measures net directional volume (buying or selling) over an entire price duration. In other words, the imbalance between the number of shares bought and sold in a given period represents the true depth of the market. This statistic shows how much one-sided volume was exchanged before the quotes exceeded the predetermined threshold (Engle & Lange, 2001).

$$VNET = \log \left| \sum_{i} (d_i vol_i) \right| \tag{27}$$

Where d is the trade direction indicator (sell = -1 and buy = 1), and vol is the number of shares traded. The sum of all transactions in a given price duration and the entire VNET equation are estimated at logarithmic levels.

4.4.1.3 Measuring of prior market performance

The analysis uses Cumulative Adjusted Return (CAR) to evaluate market performance. The aftermath period returns are calculated based on Ritter (1991).
The market-adjusted return for index i in the t^{th} trading week is determined to be:

$$ar_{it} = r_{it} - r_{mt} \tag{28}$$

Where r_{it} is the return of index i in the t^{th} trading week and r_{mt} is the average return of the index in the month.

The average market-adjusted return on a sample of n stocks for the n^{th} event month is the equally weighted arithmetic average of the market-adjusted returns for each trading month and is calculated as follows:

$$\overline{ARR_T} = \frac{1}{n}\sum_{i=T}^{n} ar_{it} \tag{29}$$

The cumulative market-adjusted return (CAR) for the aftermath market performance from month 1 to month T is the total market-adjusted return. CAR is calculated by adding the average market-adjusted returns (ARR_T) over different time periods. CAR from event month q to event month s is the summation of the average monthly adjusted returns:

$$CAR_{q,s} = \sum_{q}^{s} \overline{ARR_T} \tag{30}$$

4.4.1.4 Measuring of market volatility

Measuring volatility is not without problems. Even the basic volatility indicators are quite complex. The amount of data required for any measure of volatility is significant. So, there are advantages and disadvantages to using any measure of volatility. Standard deviation, the most common and practical measure of volatility, has been discussed. The standard deviation or variance of financial returns is often used as a proxy for risk (Campbell, 2004; Ahmed & Sarfraz, 2018). One must first choose the time period to evaluate returns to calculate the standard deviation. The standard deviation can be calculated using the following formula:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(r_i - \bar{r})^2}{n-1}} \tag{31}$$

Where r_i is the rate of return for the week i; $\bar{r}$ is the average return for the market, and n is the sample size.

The main advantage of standard deviation is that it is well-known and understood by everyone. It can be quickly calculated and retrieved from various sources (for example, spreadsheets and calculators). However, the effectiveness of this measure becomes less certain as the time shortens. Calculating the mean return over the study period is also necessary. In addition, the pertinent period and relevant return deadline must be clearly stated.

In this study, the assessment of market volatility is constructed using the method of French, Schwert, and Stambaugh (1987), previously used by Statman, Thorley, and Vorkink (2006) and Shah, Raza, and Khurshid (2012). According to French, Schwert and Stambaugh (1987), the formula for calculating market volatility $Msig^2$ is:

$$Msig^2 = \sum_{t=1}^{N} r_t^2 + 2 \sum_{t=1}^{N-1} r_t r_{t+1} \tag{32}$$

Where there are N weekly returns, r_t in the sample.

4.4.1.5 Robustness of the model

The study tested the Investor Overconfidence Index with other existing measures of investor overconfidence to confirm the usefulness of the index and the accuracy of the results. The previous VAR model used by Statman, Thorley, and Vorkink (2006) was applied to the return series. This was done to see if the index gives qualitatively comparable results.

4.4.2 Objective 2: Compare the varying degree of investor overconfidence in selected African stock markets

Once investor overconfidence had been established, studying how it changed depending on market conditions was necessary. To achieve this, the study tested the asymmetric response of trading volume to stock market returns in different market environments (normal, bullish, bearish). Current market trading volume and lagged stock market returns are assumed to be positively related (Chuang & Lee, 2006; Metwally & Darwish, 2015).

It is necessary to evaluate the sensitivity of the return-volume relationship to changing market conditions. According to Chen (2012), the asymmetric volume-return nexus is supported by two different dynamics in financial analysis. The first view is that cyclical changes in stock market returns are well documented in the literature, with empirical evidence demonstrating that non-linear regime-switching models fit the data better than linear models. On the other hand, because the volume-return relationship reflects the structure of financial markets, different market conditions may lead to different investor behaviours; therefore, the relationship is expected to change during different phases of the market cycle (Chen, 2012). Therefore, past and sustained successes in the stock market are expected to reinforce investors' overconfidence, which would lead to a positive volume-return relationship. Two models were used to explore this asymmetry: the Generalized Methods of Moments (GMM) regression model of Chuang and Lee (2006) and the Markov Switching Time Series Vector Autoregressive (MS-VAR) model by Chen (2012).

4.4.2.1 Regression analysis

Gervais and Odean's (2001) learning model predicts that investor overconfidence and its main side effect, increased trading, are likely to increase in later periods (or immediately after) of a bull market. This implies that the positive relationship between lagged market returns and current trading volume would be stronger in the later (or immediately following) periods of a bull market than in other market periods (Chuang & Lee (2006). The following regressing model previously used by Chuang & Lee (2006) was employed:

$$V_t = \alpha_0 + \alpha_1 |R_t| + \alpha_2 MAD_t + \alpha_3 R_t + \alpha_4 (D_{zt} * |R_t|) + \alpha_5 (D_{zt} * MAD_t) + \alpha_6 (D_{zt} * R_t) + \sum_{j=1}^{p} \beta_j + \sum_{j=1}^{p} \gamma_j \, (D_{zt} * R_{t-j}) + \varepsilon_t \qquad (33)$$

Where V_t represents trading volume, R_t is the market-wide return, |R| the absolute value of R_t, MAD_t means the absolute return deviations, deviation, ε_t is the residual term. Trading volume is measured as follows:

$$V_t = Log\left(\frac{Vo_t}{Vo_{t-1}}\right) \qquad (34)$$

Where Vo_t and Vo_{t-1} are the current and previous volume of the index at time *t* and *t-1*

$$MAD_t = \frac{\sum_i^N |R_{it} - R_t|}{N} \qquad (35)$$

Where R_{it} represents weekly return i, average return, R_t and N is the total number of variables in the sample. Schwarz Bayesian Criterion (SBIC) and Akaike Information Criterion (AIC) were used to select the number of lags, p.

Like previous studies, the present study uses the absolute value of returns and the mean absolute deviation as control variables for the relationship between trading volume and stock market volatility. According to Chuang and Lee (2006) and Rahma and Scalera (2019) $|R_t|$ and MAD_t are the control variables to control the relationship between the volume of transactions and the stock return volatility. According to Karpoff's (1987) literature review of the contemporary volume-volatility relationship, the first control variable, $|R_t|$ has been created. The second control variable MAD_t is inspired by Ross (1989), who hypothesised that in a frictionless market with no arbitrage potential, the rate of information diffusion can be inferred from price fluctuations or volatility. The variable D_{zt} is a dummy variable reflecting different market states, taking the value equal to one or zero. It is equal to 1 during bullish periods and equal to 0 during bearish periods.

To estimate equation (33), the study used the Generalized Method of Moments (GMM) to estimate the coefficients and standard errors using the covariance matrix specified by Newey and West (1987). This procedure produces a consistent covariance matrix in the presence of conditional heteroscedasticity and autocorrelation. To test the investor overconfidence hypothesis, the study focused on the null hypothesis that lagged stock market returns do not affect current trading volume. For example, the null hypothesis that $\beta_j = 0$ for all j, is tested using the Wald test statistic, an asymptotic chi-square statistic with degrees of freedom equal to the number of constraints. The χ^2_β and χ^2_γ test statistics were used to test the null hypothesis that $\beta_1 + \beta_2 + \beta_3 = 0$ and that $\gamma_1 + \gamma_2 + \gamma_3 = 0$, respectively. The test statistic $\chi^2_{\beta\gamma}$ was used to test the null hypothesis that the sum of all estimated coefficients β_j and γ_j is zero. The positive (minus) γ_j constants quantify the increasing (decreasing) influence of past stock market returns on trading volume in bull markets compared to bear markets. The β_j coefficients measure the correlation between past stock market returns and current trading volume in a bear market. When the expected γ_j constants are substantially negative, this means that individuals trade less actively trading in the bear market, while significantly positive γ_j constants mean that individuals are trading more actively in the bull markets, consistent with the investor overconfidence theorem. The study estimated seven regressions and compared the results.

4.4.2.2 Regime Switching Vector Auto Regression Model

Another method to analyse investor overconfidence under different market conditions is to subject stock market returns to regime switching. According to Krolzig (2000), regime-switching provides better forecasts than traditional linear models. The study used a Markov Switching Vector Autoregression (MS-VAR) model to establish the asymmetry between stock market returns and trading volume, which allows for possible regime shifts in the relationship between the variables. A regime-switching time series VAR was measured to detect directional changes in the return-volume link and potential variations over time in these cause-and-effect patterns.

A two-state MS-AR(q) model (Hamilton, 1989) is used first to identify bearish and bullish regimes, and then the potential for an asymmetric return-volume relationship is investigated. According to Maheu and McCurdy (2000) and Perez-Quiros and Timmermann (2000), stable stock market conditions with high returns are called bull markets, while chaotic conditions with low returns are called bear markets.

The MS-AR (q)) is as follows:

$$\varphi(L)r_t = \mu_{st} + \beta_{st}V_{st} + \varepsilon_t, \qquad \varepsilon_t \sim i.i.d\ N(0, \delta_{st}^2) \tag{36}$$

Where r_t is the stock market return, V_t is the trading volume

$\varphi(L) = 1 - \varphi_1(L) - \varphi_2(L^2) - \cdots - \varphi_q(L^q)$, L represents Lag operator.

The variables δ_{st}^2 and μ_{st} represent the state-dependent variance and mean of r_t respectively. The dummy variable s_t is an unobserved state term that takes the value one or zero. Given $s_t = 0\ or\ 1$ indicates a bearish or bullish market, respectively. The following fixed transition probability matrix describes a two-state Markov process followed by the stock returns.

$$P = \begin{bmatrix} P^{00} & 1 - P^{11} \\ 1 - P^{00} & P^{11} \end{bmatrix} \tag{37}$$

Where:

$$P^{00} = P(s_t = 0 | s_{t-1} = 0) \tag{38}$$

$$P^{11} = P(s_t = 1 | s_{t-1} = 1) \tag{39}$$

The study used the bivariate Markov switching autoregression (MS-VAR) model of Krolzig (1997), which was also previously used by Bahloul, Mroua, and Naifar (2017).
The MS-VAR model is written as:

$$R_t = \mu_{1st} + \sum_{j=1}^{p} a_{jst} R_{t-j} + \sum_{j=1}^{p} b_{jst} V_{t-j} + \varepsilon_{1t} \tag{40}$$

$$V_t = \mu_{2st} + \sum_{j=1}^{p} c_{jst} R_{t-j} + \sum_{j=1}^{p} d_{jst} V_{t-j} + \varepsilon_{2t} \tag{41}$$

R_t represents the weekly stock market index returns, V_t represents the stock market trading volume and ε_{it} , $i = 1{,}2$ represents the white noise process with mean zero and variance dependent on the regime s_t. Akaike information criterion (AIC) and Schwarz Bayesian Criterion (SBIC) determine the optimal lag length. P represents the order of the corresponding lag variable. The cause-and-effect relationship between two variables R_t and V_t is expressed in terms of predictability. Therefore, V_t causes R_t in a particular regime if at least one of the b_j,j =1…p is significantly different from zero in that regime, and R_t causes V_t in a given state if at least one of the c_j , j =1…p significantly differs from zero in that regime. The MS-VAR model can generate P regression models, linking each model to at least two regimes, bullish and bearish, and showing in which regime the overconfidence is significant for the investors.

4.4.3 Objective 3: Modelling stock return volatility through investor overconfidence and market conditions

The third objective was to identify the causes of excessive volatility observed in the African stock markets in the face of investor overconfidence. Trades made by overconfident individuals are expected to increase asset volatility. It remains to be seen whether excessive trading by overconfident investors is responsible for excessive volatility in market returns. However, it should be emphasised that excessive volatility is not always the result of excessive trading by overconfident investors. Several studies, including Benos (1998) and Chuang & Lee (2006), classify the contributions of overconfident investors, liquidity traders, and rational investors to the trading volume. Chuang and Lee (2006), Sheikh and Riaz (2012) and Rahma and Scalera (2019) divide the trading volume into two components, one due to excess trading by overconfident investors and the other remaining due to other factors. To distinguish the impact of overconfident investors on the total trading volume, the following regression model was used:

$$V_t = \alpha + \sum_{j=1}^{p} \beta_j R_{t-j} + \varepsilon_t \tag{42}$$

$$V_t = \left[\sum_{j=1}^{p} \beta_j R_{t-j}\right] + \ [\alpha + \varepsilon_t]$$

$$V_t = [OVER_t] + [NONOVER_t]$$

Where V_t is turnover, R_{t-j} is past return. The sum of the constant with the residual component $[\alpha + \varepsilon_t]$ represents the fraction of trading volume that is not related to investor overconfidence ($NONOVER_t$). The remaining component ($OVER_t$) represents the portion associated with overconfident investors due to lagged market returns. Like previous studies of Chuang and Lee (2006), Sheikh and Riaz (2012) and Rahma and Scalera (2019), the current study combined the two variables $NONOVER_t$ and $OVER_t$ into the variance equation of the Exponential Generalised Autoregressive Conditional Heteroskedasticity (EGARCH) model that was proposed by Nelson (1991) and the Threshold Autoregressive Conditional Heteroskedasticity (TARCH) model that was proposed independently by Glosten, Ravi, and Runkle (1993) and Zakoian (1994). This helps analyse the impact of investor overconfidence on excessive volatility. These models consider the asymmetric response of volatility to changes in the return sign. They consider the possibility that return volatility increases more in response to a negative return shock than to a positive return shock of the same magnitude (Sheikh & Riaz, 2012). Models in the GARCH family can capture the most desirable features of stock market return data, including leverage effect, leptokurtosis, and volatility clustering (Brooks, 2019). These models enable the modelling and prediction of conditional variances, capture the possibility for clustering of volatilities, and incorporate heteroscedasticity into the estimation process (Brooks, 2019).

4.4.3.1 Symmetric GARCH model

The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model is specified from the independent work of Bollerslev (1986) and Taylor (1986), in which the current conditional variance depends on q lags of the square of the residual and p lags of the conditional variance such that GARCH (p, q), has the following form:

$$R_t = \mu_t + \varepsilon_t$$

$$R_t = \alpha + \beta R_{t-1} + \gamma\varepsilon_{t-1} + \varepsilon_t$$

$$\varepsilon_t \,|\big(V_t, \varepsilon_{t-1,} \, \varepsilon_{t-2}, \dots \, R_{t-1}, R_{t-2}, \dots\big) \sim GED(0, h_t),$$

$$\ln h_t = \omega + \sum_{j=1}^{p} \alpha_j \, \varepsilon_{t-j}^2 + \sum_{i=1}^{q} \beta_i \ln h_{t-i} + f_1 NONOVER + f_2 OVER \qquad (43)$$

The variable V_t represents the market trading volume, R_t, is the current week's market return, R_{t-1} is the previous week's market return, and μ_t is the mean of R_t (expected return) conditional/based on past information, ε_t represents the unexpected return (or forecast error) and h_t represents the conditional volatility. The coefficient α represents the systematic impact of the model. The coefficient β measures the continuance in conditional volatility. The coefficient f_1 reflects other potential explanations for excessive volatility, while the parameter f_2 captures the impact of investor overconfidence on excess volatility. Due to the shortcomings of GARCH (q, p), several extensions have been created. These shortcomings arise from failing to provide feedback between the conditional variance and the conditional mean, the inability to account for the leverage effect, and the possible violation of non-negative conditions.

4.4.3.2 Asymmetric GARCH models

The most popular and widely used asymmetric models chosen for this study are the EGARCH and the TARCH. They can overcome the shortcomings of the GARCH model. The GARCH model assumes that the impact of positive and negative shocks on volatility is the same, as they depend on the square of the residuals from the previous period and the conditional variance of the previous period. For stock market returns, there is a tendency for a negative shock to cause volatility to increase returns more than a positive shock of the same magnitude, often attributed to the leverage effect (Brooks, 2019).

- **EGARCH**

The EGARCH model was introduced by Nelson (1991). The model has the following form:
ARMA (1,1)-EGARCH (1,1)

$$\ln h_t = \omega + \eta \left(\frac{|\varepsilon_{t-1}| + k\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right) + \delta \ln h_{t-1} + f_1 NONOVER + f_2 OVER \quad (44)$$

The volatility parameter k captures the asymmetric effect in the EGARCH model. If $k < 0$, then conditional volatility tends to decrease (increase) when the standardised residual return is positive (negative).

- **TARCH**

The TARCH model is another volatility model that can capture asymmetric effects and be used as an alternative.
The TARCH model has the following form:

ARMA (1,1)-TARCH (1,1)

$$h_t = \omega + \eta\varepsilon_{t-1}^2 + \theta d_{t-1} (\varepsilon_{t-1}^2) + \delta h_{t-1} + + f_1 NONOVER + f_2 OVER \quad (45)$$

The dummy variabled_{t-1} takes the value 0 if $\varepsilon_{t-1} \geq 0$ and is equal to one if when $\varepsilon_{t-1} < 0$. Henceforth, if $\theta < 0$, positive (negative) residual return innovations ε_{t-1} would have a smaller (larger) impact on volatility than negative (positive) innovations.

Equations 43-45 and Equation 42 help distinguish additional factors influencing stock market volatility from excessive trading by overconfident investors. The parameter f_1 measures the impact of other factors on excessive volatility, while parameter f_2 measures the impact of investor overconfidence on stock market volatility. If trading volume due to investor overconfidence adds to the conditional volatility of stock market returns, then $f_2 > f_1 > 0$. The conditional errors are assumed to follow Nelson's generalized error distribution (GED) (1991).

4.4.3.3 Rolling Regression Analysis

The final stage was to determine whether, as predicted by AMH, the patterns of investor overconfidence change over time. Evanthia (2017) notes that rolling window estimation is a new phenomenon in market anomaly modelling. Rolling estimations were used to evaluate constants and how their magnitudes have changed over time. The two main characteristics of rolling estimation are window size and step. The window represents the number of consecutive observations used for each regression, while the step represents the number of increments between consecutive rolling windows. The appropriate model for each window was selected from equations 43, 44 and 45. To collect enough data and produce reliable results to explain changes in the investor overconfidence behaviour over time, rolling regression estimations were performed on a 3-year fixed rolling window that was advanced by one year. The study used three three-year rolling windows (window size), rolled forward by one year (step size), and dropped the furthest year to detect overconfident investor behaviour over time. Urquhart and McGroarty (2014) argue that the suitability of a one-year step for assessing the evolution of market efficiency has been demonstrated in the literature. The first estimate was based on a window period that spans from 2005 to 2007. The second estimate spanned from 2006 to 2008, followed by 2007 to 2009 until the end of 2019. The three-year period generates about 144 weekly data observations, enough to produce robust results.

4.5 Summary

This section provides quantitative assessments of investor overconfidence in the selected African stock markets from an AMH perspective. The chapter provides details on data sources and calculation methods. The 15-year sample period of the study is from January 2005 to December 2019. Seven stock market indices, namely MOSENEW, EGX30, JALSH, NGXINDX, NSEASI, GGSECI and SEMDEX returns were examined in the study. Before running the investor overconfidence models, preliminary tests and diagnostics were performed. The tests for normality, stationarity, autocorrelation, and heterogeneity were discussed. The chapter examines various tests to compare the varying levels of investor overconfidence in several African stock markets. They include the GMM dummy regression model for the return-volume relationship and market conditions and explain how to create variables such as bullish and bearish conditions. Furthermore, this chapter explains how the MS-VAR model was applied in investigating investor overconfidence in market conditions and its applicability in testing the AMH. This model can consider the desirable characteristics of stock market returns and reveal the overconfidence behaviour of investors under different market conditions.

The chapter also covers a variety of tests used to determine how investor overconfidence affects the volatility of stock market returns. The process of selecting the optimal model and testing hypotheses was detailed, along with an explanation of the various GARCH models used to assess investor overconfidence. Because they can capture market return characteristics that linear OLS regression models cannot capture, GARCH family models were preferred. Additionally, it describes how the rolling window method was used in these experiments to account for time variance. Serve to demonstrate that the selected models can be used to study the AMH paradigm. The results, interpretation and analysis of the different model estimation strategies discussed in this chapter are presented in the following chapter (chapter 5).

CHAPTER 5: RESULTS ANALYSIS AND DISCUSSION

5.1 Introduction

To address the study's research questions, the present chapter analyses the estimations' results using the empirical methodology described in the previous chapter. This chapter fully explains the results and their analysis and interpretation. Before analysing the results of the estimated models, a preliminary experimental and diagnostic test analysis is presented to ensure that the data used are appropriate for this study. The chapter is divided into six sections. The descriptive statistics are covered in the first section, followed by a discussion of tests for serial correlation and heteroscedasticity. The results of assessing the level of investor overconfidence are presented in the second section. The findings from regression studies and regime switching vector auto-regression analysis are presented in the third section, which aims to compare different levels of investor overconfidence. The fourth section presents and discusses the results of modelling stock return volatility through investor overconfidence and market conditions in the selected African stock markets. The rolling window GARCH estimation results are presented in the fifth section to determine whether the hypothesised patterns of investor overconfidence in the AMH change over time. A brief overview of the findings and contents of the entire chapter is given in the final section.

5.2 Descriptive statistics

It is useful to be able to summarise the important characteristics of a series using a small number of summary measures when analysing a series with a lot of data. This section discusses the statistics most frequently used to describe financial and economic series, sometimes called summary statistics or descriptive statistics (Brooks, 2019). According to Lacourreye, Jankowski and Lisan (2020), the method of developing hypotheses and selecting research variables in evidence-based medicine uses descriptive statistics as the basis of logical reasoning and is a key element. Table 5.1 contains descriptive information on performance indicators (return indices) over the entire study period.

The seven markets' average weekly returns were all in the green, which suggests that the market was growing during the study period and pointed to a bullish market. However, all real average returns are practically zero. This can be attributed to the global financial crisis of 2007 - 2008, the European sovereign debt crisis of 2008 – 2012, and the Arab uprisings of 2010 - 2011. The highest mean weekly return is for MOSENEW, followed by SEMDEX and JALSH.

The lowest weekly mean return is for NGXINDX. The NGXINDX and EGX30 have the most variable returns, but the risk patterns do not match the return patterns. Even though they have maximum volatility, their weekly returns are low. This suggests that risk is not a commonly priced factor in these markets, as measured by the standard deviation. This can be a sign of noise trading and goes against the idea that risk brings greater rewards, high risk, and high returns. Since NGXINDX has high mean weekly returns and is also highly volatile, it is consistent with the return model. This is not a surprising phenomenon because it is one of Africa's most liquid stock markets. According to the standard deviation, the NSEASI and the GGSECI volatility are comparable. The JALSH has the least volatile returns.

The assumption of normality was tested using the Jarque-Bera (JB) test. A normally distributed series must have a skewness of 0 and a kurtosis of 3 for it to be symmetric about the mean. While K values of less or greater than three indicates a flat or peaked distribution, respectively, a negative or positive S distribution in the series indicates the presence of asymmetry in the return data. Four of the seven markets are positively skewed showing longer right tails. This shows that more of the market's weekly returns are above average. Returns in the other three markets are negatively skewed. These skewed results, both positive and negative, show that there are asymmetries in the returns data.

This indicates that there were more significant departures from the mean than would be expected from a normal distribution. These results regarding skewness and kurtosis are supported by the JB tests, which rejected the null hypothesis of normal distribution for each series. This result shows that the distribution of returns in these markets is leptokurtic, with very high means and longer tails than a normal distribution would predict. The leptokurtic distribution of EGX30 was the highest, followed by NGXINDX and MOSENEW, which was the lowest. Table 5.1 also presents the results of the JB test as further evidence of the non-normality of the return series, as suggested by S and K. The significance of Jarque-Bera's data is discussed. The null hypothesis is rejected because the p-value of the JB statistic is less than 1%, indicating that the return series is not normally distributed.

Table 5.1 also includes the results of the stationarity test and the unit root test. The ADF and the KPSS unit root test determine whether the weekly market return series used in the GARCH family of models is stationary. The results show that all market ADF test statistics are significant at the 1% significance level, as their corresponding critical values are less than 0.01.

As a result, the alternative hypothesis of stationarity was accepted in place of the null hypothesis of the existence of a unit root. As opposed to the ADF test, the KPSS tested the null hypothesis of stationarity against alternative hypothesis of unit root. All the KPSS test statistics from the weekly return series are insignificant.

The study failed to reject the null hypothesis of stationarity in levels in favour of the alternative hypothesis, according to which the series would have a unit root because the test statistic is significantly smaller than the critical value. Accordingly, the market returns were used to estimate the GARCH family of models. These KPSS results also confirm the results of the ADF test, indicating that the series is stationary across levels. Likewise, the results show that stationary time series can be used to estimate VAR models because they would not produce inaccurate or spurious regressions. Since the series is stationary, there would not be cointegration problems between market turnover and market returns. Therefore, the VAR models were safely used to estimate the long-run relationship between variables accurately, and it was not necessary to use a vector error correction model (VECM).

Table 5.1. Descriptive statistics for the weekly returns for the selected African markets

	RETURNS EGX30	RETURNS GGSECI	RETURNS JALSH	RETURNS MOSENEW	RETURNS NGXINDX	RETURNS NSEASI	RETURNS SEMDEX
Mean	0.001876	0.000473	0.001931	0.002197	-9.12E-05	0.001154	0.002159
Median	0.003966	-1.08E-05	0.002842	0.001967	0.000279	0.001600	0.000313
Maximum	0.165809	0.185955	0.160396	0.112849	0.150320	0.236446	0.095442
Minimum	-0.410758	-0.147549	-0.096347	-0.123013	-0.307373	-0.125775	-0.178391
Std. Dev.	0.046044	0.033089	0.024579	0.027389	0.041985	0.033660	0.028241
Skewness	-1.429345	0.318396	0.050607	-0.028790	-0.889077	0.364923	-0.429915
Kurtosis	12.99453	6.271319	7.295148	4.079877	9.539689	7.527124	6.503867
Jarque-Bera	3516.539	217.0499	600.6717	38.05588	1494.618	540.5826	423.5750
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

Sum	1.465258	0.222014	1.507805	1.715627	-0.071243	0.711814	1.686153
Sum Sq. Dev.	1.653654	0.512405	0.471236	0.585118	1.374957	0.697945	0.622111
ADF	-30.61812 ***	-18.89988 ***	-30.13709 ***	-28.83734 ***	-26.72487 ***	-26.48093 ***	-28.49549 ***
KPSS	0.242125	0.222456	0.212482	0.501490	0.172543	0.209106	0.248679
Observations	781	469	781	781	781	617	781

The critical values for the ADF and KPSS tests were taken from MacKinnon (1996) and Kwiatkowski-Phillips-Schmidt-Shin (1992).

Significance is indicated by ***, ** and * at the 1%, 5% and 10% levels respectively.

Source: Author (2023)

For the seven selected markets, the weekly return plots are shown in Figure 5.1 below. The stock return chart shows that, as the AMH predicted, the variance changes over time and exhibits an autoregressive pattern, causing volatility clustering across all the markets. These charts show that some periods (times) appear riskier than others due to the higher return volatility during those times (periods). These riskier periods, common in all the markets, correspond to key events such as the 2007-2008 global financial crisis, the 2010-2011 Arab revolution and the Eurozone debt crisis of 2008-2012. On the other hand, since all the plots have constant mean values throughout the sampling period, they support the stationarity of the series.

Due to high volatility, the Egyptian and Nigerian stock return plots appear riskier than all the other markets. The year 2011 was also marked by an uprising in Egypt, leading to the collapse of the stock market bubble and the value of shares traded on the Egyptian stock exchange at that time plummeted by 6.25% (Abdeldayem, 2015). This may help explain why its returns were more volatile over the period under review than those of the other markets. According to a model created by Pastor and Veronesi (2006), firms experiencing bubbles are characterised by highly volatile and unpredictable returns. The return graph indicates that the NSEASI and the GGSECI volatility levels are comparable. The JALSH has the least volatile returns.

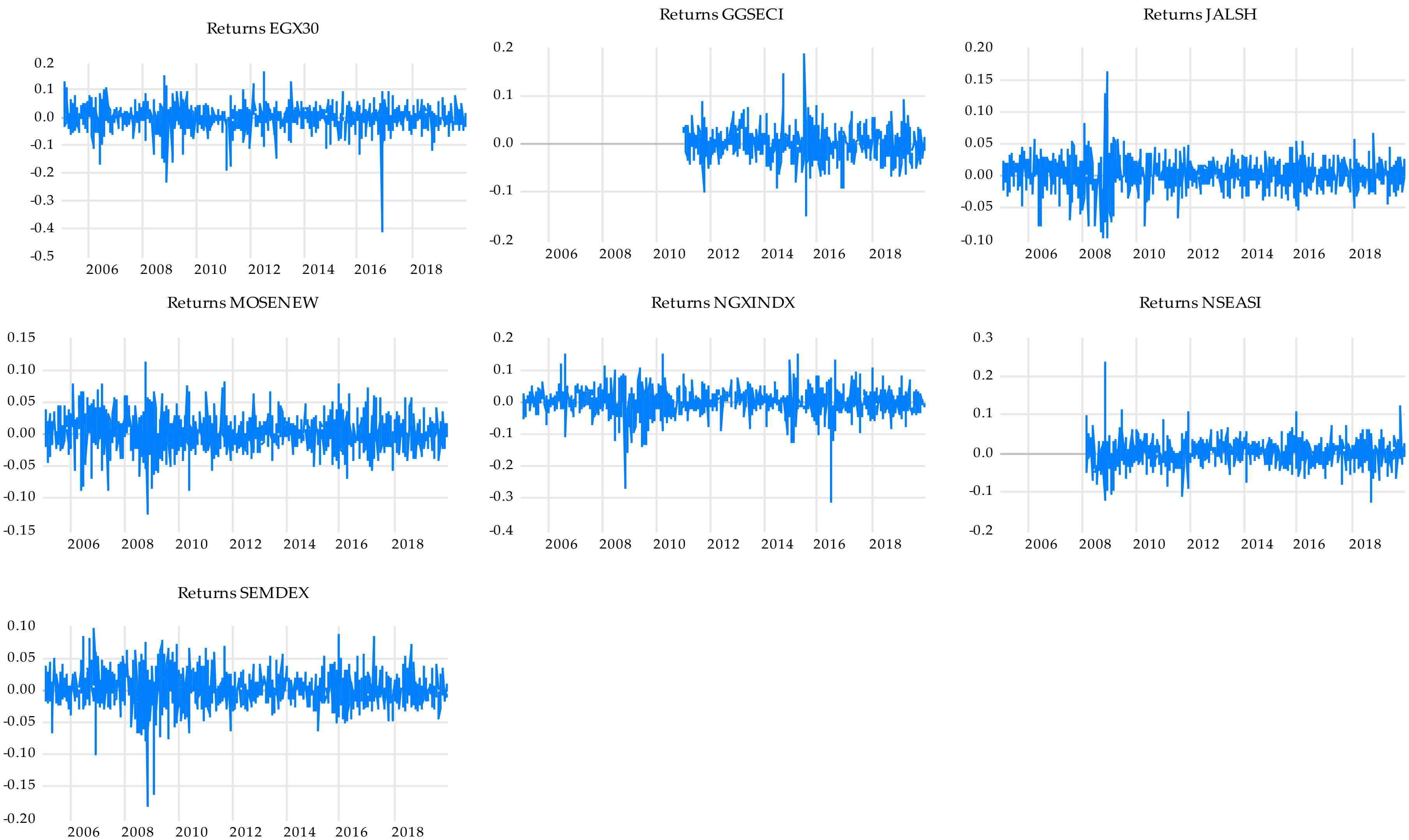

Figure 5.1 Weekly return series for the selected African markets

Source: Author (2023)

5.3 Serial correlation and Heteroscedasticity

In addition to the above descriptive statistics, ARCH effects and autocorrelation tests were performed on the broad market indices. The results of these two assessments are listed in Table 5.2 below. Except for the MOSENEW, NSEASI and the SEMDEX, all the series showed signs of serial correlation according to the Ljung-Box (LB) test results. An indication of market price momentum would be a positive and statistically significant serial correlation, implying that the returns in a period are more likely to be positive (negative) if the returns in the period before were positive (negative). Stocks with the highest trading volume have the strongest price momentum. In other words, price changes associated with high volume are more likely to persist into the next period (Stickel & Verecchia, 1994). These results refute Fama's (1970) assertion that information is efficient and demonstrate the inefficiency in the return series of the EGX30, the GGSECI, the JALSH, and the NGXINDX. According to the EMH, if markets are at least weak form efficient, stock prices should accurately reflect all the information contained in previous prices about future prices. In this situation, deriving information from past prices makes predicting future prices or extrapolating future earnings difficult (Fama, 1970).

Serial correlations can sometimes be exploited from an investment strategy perspective to generate excess returns. Positive serial correlations can be exploited by a strategy of buying after periods of positive returns and selling after periods of negative returns. In the case of negative serial correlations, a buying strategy would be recommended after periods of low returns, and a selling strategy would be recommended after periods of high returns. There is no serial correlation between the MOSENEW, the NSEASI and the SEMDEX, suggesting that these markets have at least a weak form level of market efficiency. This means that information from previous prices has been factored into the current cost. In this scenario, it would be difficult to extrapolate future earnings from past or future stock prices. Therefore, the returns are essentially white noise (Granger, 2005).

The Breusch-Godfrey serial correlation LM (Godfrey, McAleer, & McKenzie, 1988) test was also performed to support these results. Since all the test statistics are significant up to lag level 6, according to Tsay (2010), this test confirmed the existence of serial correlation in the returns of the EGX30, the GGSECI, the JALSH and the NGXINDX except for the MOSENEW, the NSEASI and the SEMDEX.

The LB statistic for the squared returns was statistically significant for all the indices. It was higher and went beyond the LB statistic for the returns. A positive autocorrelation across several weeks is indicated by a stronger autocorrelation in terms of the squared returns, indicating the likelihood of high volatility events clustering over time (Cont, 2001). These results may explain the leptokurtic distribution observed in the return series in the descriptive statistics Section 5.2 described above (Brooks, 2019). The Autoregressive Moving Average (ARMA) structure in generalized autoregressive conditional heteroskedasticity (GARCH) models should also be modelled using the serial correlation results. The serial correlation results of the squared returns show the presence of heteroskedasticity and indicate that the second moments of the return series portray the AMH over time.

The alternative that the series is described by the ARCH(L) model was contrasted with the null hypothesis, that the residual series does not exhibit conditional heteroscedasticity (ARCH effects), using the ARCH test of Engle (1982). The LM test statistic was significant for each series, indicating that the ARCH effects were present in all the series according to the test results. Accordingly, these results are consistent with the LB test on squared returns. Based on the results of these two experiments, the conditional volatility of these stock market return series was simulated using the GARCH family models because they capture the time-varying conditional volatility that follows an autoregressive process.

Table 5.2 Serial Correlation and Heteroscedasticity test for the chosen markets

	LB statistic	LB^2 statistic	Breusch-Godfrey LM statistic	Engle ARCH LM statistic
RETURNS EGX30	11.768 *	12.527 *	11.9096 *	10.75180 *
RETURNS GGSECI	11.586 *	32.632 ***	11.58451 *	30.67572 ***
RETURNS JALSH	16.329 **	415.68 ***	14.722 **	179.6729 ***
RETURNS MOSENEW	6.3043	92.817 ***	6.4523	61.32786 ***
RETURNS NGXINDX	13.812 **	43.028 ***	12.80966 **	31.57704 ***
RETURNS NSEASI	4.3661	35.460 ***	4.656201	34.094 ***
RETURNS SEMDEX	2.8167	50.143 ***	2.820814	39.87420 ***

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. LB and LB^2 represent the Ljung-Box statistics for the returns and squared returns, respectively. All four tests were performed with 6 lags, as per Tsay (2010).

Source: Author (2023)

5.4 Measurement of Investor Overconfidence

The investor overconfidence index and the values of the components used to calculate the index are presented in Table 5.3 below. The estimates show that all the markets have high average market turnover, which indicates active trading activity in the African equity markets. The highest market turnover ratio is held by the GGSECI, followed by the SEMDEX and the JALSH. The EGX30 and the NGXINDX are the markets with the lowest market turnovers. These observations support the theory of investor overconfidence, in which lagged market returns are assumed to be positively related to current market turnover. Previous studies have shown that higher trading volumes in the stock markets are due to excessive investor confidence influenced by favourable prior market performance. These results are not surprising because the assessment of average market returns performed in Section 5.1 (discussed earlier) showed positive returns, often considered the source of encouragement for overconfident investors to participate in aggressive trading. This result is consistent with several studies that have examined the possibility that overconfident investors may trade more aggressively after a period of positive market results.

Gervais and Odean (2001), Statman, Thorley, and Vorkink (2006), Chuang and Susmel (2011), My, Toan, and Cuong (2016), and Chen and Sabherwal (2019), among others, contend that the positive lead-lag relationship between stock market returns and market trading volume indicates the presence of investor overconfidence, supports this finding. The relationship between stock market turnover and stock market returns was examined by Statman, Thorley, and Vorkink (2006) using the VAR model and the corresponding impulse response functions. The regressed VAR model showed that the lagged market returns have a significant positive relationship with current market turnover over the entire sample period, consistent with the investor overconfidence hypothesis. According to Metwally and Darwish (2015), market conditions, as predicted by the AMH, significantly impact trading activity in the Egyptian stock market.

According to the study, trading activity is specifically triggered when the Egyptian stock market is upward or has good returns. Zaine (2013) finds out that trading volume is influenced by lagged stock market returns over months using market returns and trading volumes in the Chinese and Tunisian stock markets. Using an impulse response function, Sheikh and Riaz (2012) and Tariq and Ulla (2013) investigated investor overconfidence in the Pakistan Stock

Exchange and found a significant association between market turnover and lagged market returns. Zia, Sindhu, and Hashmi's (2017) findings on investor overconfidence behaviour in the Pakistani stock market show that investors are overconfident because turnover directly correlates with stock returns. In their investigation of the Saudi stock market into the presence of investor overconfidence, Alsabban and Alarfaj (2019) found evidence that favourable stock market returns influence market turnover.

The market volatility results measured by $MSig^2$ show that all the markets are volatile. The NGXINDX and the EGX30 had the highest volatility returns, both reaching 15%. The JALSH and the MOSENEW show the least volatile returns, while the NSEASI and the GGSECI show comparable volatility levels. Considering the levels of volatility observed in different stock markets in various locations, such as 7% in Hong Kong, 15% in Germany, and 16% in the United States (Statman, Thorley, & Vorkink, 2006; Chen & Zhang, 2011; Zoe, 2016), these results were not unexpected. These results further support the investor overconfidence hypothesis, which states that market gains are followed by high trading activity and that trading volume caused by investor overconfidence leads to excess volatility. The study of Chuang and Lee (2006) validates these findings, who found that trading volume caused by investor overconfidence adds to observed conditional volatility on the NYSE and AMEX markets. Empirically, overconfident trading shows a positive and strong correlation with volatility. Jlassia, Naouib, and Mansour (2014) examined the impact of investor overconfidence behaviour on dynamic market volatility in the global financial markets and found that the investor overconfidence bias explains a significant portion of the excessive and asymmetric volatility in the market.

The results of the market depth study show that there is no deep market. The African stock markets are said to be illiquid and inefficient (Ntim, 2012), so it is not surprising that their market depth ratio, as determined by VNet, is low. These findings are consistent with those of the South African National Treasury (2018), which states that although the African equity markets lack liquidity, pricing providers and depth, they are still fair, operate effectively and have high integrity. According to Afego (2015), all other stock exchanges remain shallow and illiquid, except for the JSE. Although the African stock markets appear illiquid, they perform admirably. According to the results, all the markets performed quite well, with the SEMDEX and the JALSH having the best overall results. The performance of the other markets appears to be at similar levels.

The investor overconfidence index was derived from the sum of all the proxy variables. Although the magnitude varies across the markets, the results demonstrate that investor overconfidence bias exists across all the African equity markets. The highest index value was found in the GGSECI, followed by the SEMDEX and the MOSENEW. The investors in the EGX30 are those with the lowest perceived investor overconfidence index. These results are consistent with the predictions of theoretical models examining investor overconfidence in African stock markets. Zaine (2013) discovered signs of excessive investor confidence in the Tunisian stock market. Additionally, Metwally & Darwish (2015) find evidence of the investor overconfidence bias in the Egyptian stock market. A study on the impact of overconfidence on investment decisions was conducted by Adel and Mariem (2013). In their study of the characteristics of the Tunisian financial market, they found that the results indicate the importance of confidence bias.

Table 5.3. The Investor Overconfidence Index

	Turnover	**Volatility**	**Market depth**	**Prior market performance**	**Index**	**Remarks**
	MTurn	**MSig**	**VNet**	**CAR**		
EGX30	0.6306	0.1546	0.2205	0.5493	1.5550	**Overconfidence**
GGSECI	0.8976	0.1331	0.2065	0.5418	1.7790	**Overconfidence**
JALSH	0.6708	0.1246	0.2216	0.5843	1.6013	**Overconfidence**
MOSENEW	0.6635	0.1274	0.2504	0.5779	1.6192	**Overconfidence**
NGXINDX	0.6387	0.1542	0.2255	0.5563	1.5747	**Overconfidence**
NSEASI	0.6473	0.1363	0.2251	0.5638	1.5725	**Overconfidence**
SEMDEX	0.6957	0.1282	0.2476	0.6060	1.6775	**Overconfidence**

Source: Author (2023)

5.4.1 Robustness checks

The study tested the investor overconfidence index with other overconfidence measures to confirm the index's validity and accuracy of the results. This was done to see if the index gives qualitatively comparable results. The study examined the lead-lag relationship between stock market returns and market turnover using the market-wide VAR model previously used by Statman, Thorley, and Vorkink (2006). Since market turnover depends directly on stock market returns, this study's results imply that investors are overconfident in all the selected African stock markets. Table 5.4 below presents the empirical results.

This investigation focused on the interaction between lagged market returns and market turnover. With an estimated parameter of 0.2326 and a confidence level of 1%, the EGX30 results comparing market turnover (Mturn) and market return (Mret) at lag 1 show that the coefficient was statistically significant. The positive impact of lagged market returns on market turnover supports the investor overconfidence theory. Other markets, GGSECI, JALSH, MOSENEW, NGXINDX, NSEASI and SEMDEX, showed similar results; all are significant in the first lag. The estimated parameters are 0.2718, 0.0252, 0.0396, 0.1679, 0.2563 and 0.3447 for the Ghana, South Africa, Morocco, Nigeria, Kenya, and Mauritius stock exchanges. The results of the VAR model confirm the occurrence of investor overconfidence behaviour in the African stock markets.

In markets outside the African continent, such as the American Stock market (Chuang & Lee, 2006; Statman, Thorley, & Vorkink, 2006), the Hong Kong Stock market (Chen & Zhang, 2011), the French Stock market (Siwar, 2011) and the Saudi Arabian Stock market (Alsabban & Alarfaj, 2019), similar results were observed. However, it seems reasonable that the investor overconfidence level varies from country to country.

The level of investor overconfidence in the VAR estimates was slightly lower and varies across countries, as the investor overconfidence index predicted. The results of the VAR estimates closely resemble those of the investor overconfidence index, such that previous tests of investor overconfidence in the African stock markets and elsewhere around the world have produced results which are consistent with the new index of investor overconfidence, thus validating the reliability of the new index.

Table 5.4: Market VAR Estimation Results for EGX30, GGSECI, JALSH, MOSENEW, NGXINDX, NSEASI, SEMDEX

	Constant	Mret (t-1)	Mturn (t-1)	Mret (t-2)	Mturn (t-2)	$Msig^2$ (t-1)
EGX30						
Mret	0.0040 *** (0.0181)	0.0558 (0.0868)	0.2326 *** (0.3328)	-0.0437 ** (0.0846)	-0.2459 (0.2762)	-0.1177 (0.0731)
Mturn	0.0168 (0.0051)	0.0602 (0.0243)	0.6456 (0.0931)	-0.0028 (0.0237)	-0.0024 (0.0773)	0.0375 (0.0205)
GGSECI						
Mret	0.3261 *** (0.5400)	-0.0216 (-0.5670)	0.2718 *** (0.8730)	0.0171 ** (-0.2520)	-0.0243 (-0.1170)	0.0621 (-0.5220)
Mturn	-0.072 (0.0000)	0.7371 (0.0000)	0.3897 (0.0000)	0.2556 (0.0000)	0.1836 (0.0000)	-0.9297 (0.0000)
JALSH						
Mret	1.1108 *** (0.0000)	0.0405 (-0.3060)	0.0252 *** (0.4950)	0.0117 ** (-0.3420)	-0.0009 (-0.8640)	0.5418 ** (0.0000)
Mturn	-8.0613 (0.0000)	-0.0585 (-0.5490)	-0.0378 (-0.6660)	0.0801 (-0.0270)	-0.0963 (-0.0090)	-0.6858 (-0.0180)
MOSENEW						
Mret	0.0518 *** (0.0085)	0.2058 (0.0843)	0.0396 ** (0.0854)	0.0851 *** (0.0025)	-0.2439 (-0.0252)	0.3055 * (0.0182)
Mturn	0.6207 (-0.2496)	3.1392 (-2.8655)	-1.4385 (-2.1824)	2.9782 (-0.0736)	3.7825407 (-0.0731)	0.5660 (-0.0202)
NGXINDX						
Mret	0.0038 *** (0.01786	0.4346 (-0.1779)	0.1679 *** (0.01801)	-0.0179 ** (0.0053)	-0.5149 * (-0.0053)	0.6450 * (-0.0038)
Mturn	1.3102 (-0.5269)	6.627181 (-2.4937)	3.0366 (0.1627)	6.2873 (-0.1552)	7.9853 (0.1543)	1.1951 (-0.0427)
NSEASI						
Mret	0.7971 *** (0.0272)	0.6634 (0.2715)	0.2563 *** (0.2750)	0.2745 (0.1582)	0.7859 (0.0008)	0.9845 (0.0105)
Mturn	1.891 (0.8042)	1.1151 (0.1220)	4.6348 (0.1436)	0.5964 (0.2362)	1.1886 (0.2356)	1.8239 (0.0652)

SEMDEX						
Mret	0.0077 *** (0.0036)	0.8921 (-0.3652)	0.3447 *** (0.3698)	-0.0368 * (0.0010)	0.1056 ** (0.0010)	1.3240 (-0.0007)
Mturn	0.6895 (0.0000)	3.6031 (0.7503)	0.2330 (0.1235)	2.9057 0.318669	16.3910 -0.316914	2.452905 -0.08775

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Source: Author (2023)

5.5 Asymmetric response of trading volume to stock market returns in bull and bear markets

According to Lo (2017), different environmental factors impact market dynamics and investor behaviour. Over the past three decades, the financial sector has devoted much attention to the relationship between stock price volatility and trading volume (return-volume relationship). This study examines if the relationship is asymmetric between bullish and bearish stock markets. It is argued that different market conditions can alter trading activity and, thus, investor overconfidence. According to Karpoff (1987), data on the return-volume relationship not only contribute to a better understanding of the structure of financial markets but also help distinguish between different competing theoretical models. Whether the AMH provides better explanations for this relationship than the popular EMH is the question of this empirical investigation. Since findings from the developed markets may not provide a good estimate of what is happening in the African stock markets, this study further examines the explanatory power of current economic and market variables on investor overconfidence in the selected African stock markets. A dummy variable was included in the two approximate equations to represent different market situations (bull and bear). The estimation results of the GMM regression and the MS-VAR models are presented in the following sections.

5.5.1 Investor overconfidence and market conditions - GMM Regression Analysis

Table 5.5, A to G, contains the results of the dummy regression, equation 37, on the relationship between stock market returns and trading volume, fitted against market conditions. The Generalised Methods of Moments forms the basis of the regression analysis, which considers two market conditions: upward-bullish and downward-bearish.

According to the empirical results presented in table 5.5. A. the tendency of investors in the EGX30 to be overconfident varies depending on the state of the market. It was found out that for market states 1, 4 and 5, representing bull markets, $\beta_1 + \beta_2 + \beta_3 > 0$, and the null hypothesis that $\beta_1 + \beta_2 + \beta_3 = 0$ is rejected at the conventional levels. The alternative that lagged market returns are driving current trading volumes is accepted and thus indicates the existence of investor overconfidence in the market. Investor overconfidence remains significant even in negative markets. According to the positive β_j coefficients quantifying the association between past stock market returns and current trading volumes in negative markets.

More importantly, the fact that the sum of $\gamma_1 + \gamma_2 + \gamma_3$ is above zero indicates that investors are overconfident, and its impact is more noticeable in bullish than bearish markets. In the case of the bear market, column 2 demonstrates that $\beta_1 + \beta_2 + \beta_3$ is significantly smaller than zero, indicating a negative correlation between lagged stock market returns and the number of current trades. For market state 3, it is also noted that $\beta_1 + \beta_2 + \beta_3 > 0$, but the sum of $\gamma_1 + \gamma_2 + \gamma_3$ is significantly less than 0, indicating that investor overconfidence does not exist and investors are less active in the negative markets. Additionally, the results show that $\sum_{j=1}^{3} \beta_j > \sum_{j=1}^{3} \gamma_j$ and that the $\chi^2_{\beta\gamma}$ test statistics, which was used to test the null hypothesis that $\sum_{j=1}^{3} \beta_j = \sum_{j=1}^{3} \gamma_j$ was rejected at the conventional levels.

These results are consistent with the predictions of the theoretical models that investor overconfidence if it exists, is likely to be more pronounced in bullish markets, and thus, it is when we are better able to detect it. This proves that the investors' overconfidence changes according to the market conditions of the Egyptian stock market, according to the AMH.

Table 5.5. B. presents the results of the GGSECI, showing that investor overconfidence is present in the market and that it changes depending on the market conditions. The observed market states 4 and 5 show strong evidence of investor overconfidence, supported by $\gamma_1 + \gamma_2 + \gamma_3 > 0$. The results show that all the estimated β_j coefficients are positive and statistically significant at the conventional levels, while the estimated γ_j coefficients are positive but not all statistically significant at the conventional levels. In the bear market state 3, the β_j coefficients are all positive except for β_3 while the γ_j coefficients are all negative except for γ_2. The χ^2_{β} and χ^2_{γ} test statistics, which were used to test the null hypothesis that

$\beta_1 + \beta_2 + \beta_3 = 0$ and that $\gamma_1 + \gamma_2 + \gamma_3 = 0$ respectively were rejected for the alternative. The results show that investors' tendency to be overconfident is common in the bull markets, and the investors trade less actively in the bear markets. These results demonstrate that market conditions impact investors' overconfidence in the Ghanaian stock market.

Experimental results are presented in Table 5.5. C. shows that market conditions influence investors' overconfidence in the JALSH. The statistical significance of the β_j coefficients together with $\beta_1 + \beta_2 + \beta_3 > 0$ during the bullish market state and one bearish period of the market implies that investor overconfidence still matters even when in the bearish market. The χ^2_β test statistics used to test the null hypothesis that $\beta_1 + \beta_2 + \beta_3 = 0$ was rejected for all the market states. It was also observed that $\beta_1 + \beta_2 + \beta_3 < 0$ during the bear market state 2. The χ^2_γ test statistics, which was used to test the null hypothesis that $\gamma_1 + \gamma_2 + \gamma_3 = 0$ was rejected for all the market states, with $\gamma_1 + \gamma_2 + \gamma_3 < 0$ in down market state 3. The negative γ_j constants quantify the decreasing influence of past stock market returns on trading volume during the bearish market. These results mean that investors are trading more actively in the bull markets and less in the bear markets, consistent with the investor overconfidence theorem. These results support AMH's assertion that investor overconfidence is not static and should appear under specific market conditions and disappear under others.

According to MOSENEW, the results are presented in Table 5.5. D., it was observed that $\beta_1 + \beta_2 + \beta_3 > 0$ in all the market states except for market state two and the null hypothesis that $\beta_1 + \beta_2 + \beta_3 = 0$ is rejected at levels because it implies that investor overconfidence remains important even in bearish market conditions. All the estimated β_j and γ_j coefficients are positive and statistically significant at all levels except for bear market states 2 and 3 and β_3 for market state 1. Most importantly, it was observed that $\gamma_1 + \gamma_2 + \gamma_3 > 0$, which implies the presence of investor overconfidence among investors in the Casablanca stock exchange. These results show that investors' overconfidence disappeared in bear market state three, where it was observed that $\gamma_1 + \gamma_2 + \gamma_3 < 0$. This proves that investors' overconfidence in the MOSENEW fluctuates cyclically according to market conditions, disappearing and reappearing when market conditions change, according to the AMH.

The influence of market conditions on investor overconfidence was found in the empirical results of the NGXINDX presented in Table 5.5. E. For all the bullish market states, it was observed that $\beta_1 + \beta_2 + \beta_3 > 0$, and the null hypothesis is that $\beta_1 + \beta_2 + \beta_3 = 0$ was rejected at levels. The null hypothesis that lagged stock returns do not drive current trading volume was rejected in favour of the alternative, demonstrating the presence of investor overconfidence. Together with the observation that $\gamma_1 + \gamma_2 + \gamma_3 > 0$, there is strong evidence of investor overconfidence in the bull market. The investor overconfidence bias was not detected in the bear market, as shown by $\gamma_1 + \gamma_2 + \gamma_3 < 0$ in market condition 3. The rejection of the null hypothesis ($\beta_j = 0$ for any j) authenticates the alternative that market stock returns cause market turnover. The rejection of the null hypothesis that lagged market returns do not cause market turnover is evidence against the market efficiency hypothesis. This vindicates Lo (2005), who argues that under the AMH theorem, market efficiency is a principle that varies according to time and market conditions.

Table 5.5. F. reports the results of the NSEASI and provides evidence that market conditions influence investor overconfidence at the Nairobi securities exchange. The results of the γ_j coefficients show that the positive value for markets 4 and 5 was statistically significant. However, the observation that the sum of the γ_j coefficients (-0.8372) in market 3 show no evidence of the investor overconfidence in the bear market. The observation that the estimated β_j coefficients are positive and statistically significant, which is evidence that even in bear markets, investor overconfidence is still present. These results show that investor overconfidence was present in Market Two, then disappeared in Market Three and was then detected in Markets Four and Five. This observation demonstrates that investor overconfidence is not static and evolves with changing market conditions.

The SEMDEX results are shown in Table 5.5. G. shows that changes in market conditions impact investor overconfidence. It was observed that $\beta_1 + \beta_2 + \beta_3 \neq 0$ and the hypothesis that $\beta_1 + \beta_2 + \beta_3 = 0$ was rejected at the significant levels, implying that investor overconfidence remains present even in periods of a bearish market state. This finding was supported by the sum of the of the γ_j coefficients $\gamma_1 + \gamma_2 + \gamma_3$ which is significantly larger than zero and illustrates the presence of investor overconfidence in the market, and its effect is more prevalent in the bull market states than in bear market states. The results show that investor overconfidence moves from a state of significant influence (market state 1), then moves to the periods of insignificant influence (market states 2 and 3), and then returns to the significant periods (market states 4 and 5). The results align with the predictions of the AMH paradigm that market efficiency fluctuates between significant and insignificant moments according to market conditions.

The results of the GMM regression analysis show that the results are consistent with the prediction of theoretical models that the investor overconfidence if it exists, may be more visible in the bullish markets than bearish markets and can be detected better at that point. The sub-period data analysis shows that the investors were overconfident immediately before the global financial crisis (2005-2007). During this period, lagged market returns significantly affected market turnover. Weak effects were observed during the crisis period (2008-2010). No investors were overconfident in the immediate post-crisis period (2011-2013), after which the lagged market returns again significantly affected the market turnover in the periods (2014-2016) and (2017-2019), showing the overconfident behaviour of investors. These results support Gervais and Odean's (2001) learning model, which predicts that investor overconfidence and its principal side effect, increased trading, are likely to rise in the late stages of or immediate period just after the bullish market. This implies that the positive relationship between lagged market returns and current market turnover is stronger during the late stages of or right after a bull market than during other market periods.

These results are consistent with the research of Chuang and Lee (2006), Chuang and Susmel (2011), Metwally and Darwish (2015), and Kumar and Prince (2022). Chuang and Lee (2006) studied the asymmetric trading behaviour of US investors and found out that investors traded more actively in the bull markets than in the bear markets. This is consistent with Daniel, Hirshleifer and Subrahmanyam's (2001) argument and Gervais and Odean's (2001) argument that the investor overconfidence bias is easily cultivated in the bull market. Chuang and Susmel (2011) assess whether investor overconfidence is more pronounced among institutional or individual investors in the Taiwan Stock Exchange. Their results show that after positive market returns, individual investors trade more frequently in bullish markets than in non-bullish markets, supporting the AMH. Metwally and Darwish (2015) examine the presence of investor overconfidence in the Egyptian stock market. Over the entire sample period, they found that the lagged market returns have a significant positive relationship with the current market turnover and thus coincide with the investor overconfidence hypothesis. Regarding the subsamples, Metwally and Darwish (2015) found that the trading activity in the Egyptian stock market is strongly influenced by market conditions, as stated by the AMH. Specifically, the study reports that investor overconfidence triggers trading activity when the Egyptian stock market is upward.

Kumar and Prince (2022) studied the overconfidence tendency of investors in India in different market scenarios: the pre-crisis period (financial crisis), the crash period and the post-crisis period. Their research shows that the investors were overconfident in the pre-crisis period, before the global stock market crash of 2008 and the duration before COVID-19 from 2015 to March 2020. In the post-crisis period, the investors were not overconfident in 2008-2010, 2010-2015 and 2020 -2021.

Table 5.5. A. Relationship between trading volume and stock returns in bull and bear markets for the Egyptian Stock Exchange

EGX30										
Market state	**1**		**2**		**3**		**4**		**5**	
	Coefficient	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**
β_1	0.3191 **	0.8334	0.3267	0.8892	0.4180 **	1.1372	0.4419	1.1700	0.4644	1.2636
β_2	0.5644	1.2438	-0.5139	-1.1493	0.5986	1.3794	0.6993 **	1.5822	0.6651 *	1.5327
β_3	-0.0415	-0.1323	0.0099	0.0297	-0.1110	0.3426	0.0855	0.2673	0.1233	0.3807
$\beta_1 + \beta_2 + \beta_3$	0.8420		-0.1773		0.9056		1.2267		1.2528	
γ_1	0.4990 ***	1.1295	-0.4869	-1.1223	-0.2811	0.6512	0.3420 **	0.7776	0.3123	0.7236
γ_2	0.2818	0.5598	-0.3582	-0.7155	0.1644 **	0.3362	0.1296	0.2628	0.1827	0.3735
γ_3	1.0271 *	2.5065	0.9927	2.3994	-0.7484	1.7844	0.8793 **	2.1204	0.8316 *	1.9827
$\gamma_1 + \gamma_2 + \gamma_3$	1.8078		0.1476		-0.8651		1.3509		1.3266	
χ^2_β	3.1122	0.0567	3.1752	0.0540	6.2743	0.0041	6.4152	0.0072	6.9714	0.0045
χ^2_γ	8.0028	0.0027	8.4753	0.0018	3.9074	0.0227	4.3686	0.0252	4.3416	0.0252
$\sum_{j=1}^{3} \beta_j + \sum_{j=1}^{3} \gamma_j$	2.6498		-0.0297		0.0405		2.5776		2.5794	
$\chi^2_{\beta\gamma}$	31.4253	0.0000	31.5135	0.0000	26.1257	0.0000	29.2833	0.0000	29.0286	0.0000
$\bar{R}^2$	0.1044		0.0643		0.0656		0.1053		0.1062	
$Q(6)$	9.8683		9.3619		8.9864		7.3275		8.6620	

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Source: Author (2023)

Table 5.5. B Relationship between trading volume and stock returns in bull and bear markets for the Ghana Stock Exchange

GGSECI										
Market state	**1**		**2**		**3**		**4**		**5**	
	Coefficient	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**
β_1	n/a	n/a	n/a	n/a	0.4551	1.2383	0.4812	1.2740	0.5057 *	1.3759
β_2	n/a	n/a	n/a	n/a	0.6518	1.5021	0.7615 **	1.7228	0.7242	1.6689
β_3	n/a	n/a	n/a	n/a	-0.1208	0.3731	0.0931	0.2911	0.1343	0.4145
$\beta_1 + \beta_2 + \beta_3$	n/a	n/a	n/a	n/a	0.9861		1.3357		1.3642	
γ_1	n/a	n/a	n/a	n/a	-0.3061	0.7091	0.3724 *	0.8467	0.3401	0.7879
γ_2	n/a	n/a	n/a	n/a	0.1790	0.3660	0.1411	0.2862	0.1989	0.4067
γ_3	n/a	n/a	n/a	n/a	-0.8150	1.9431	0.9575 **	2.3089	0.9055 ***	2.1589
$\gamma_1 + \gamma_2 + \gamma_3$	n/a	n/a	n/a	n/a	-0.9420		1.4710		1.4445	
χ^2_β	n/a	n/a	n/a	n/a	6.8320	0.0044	6.9854	0.0078	7.5911	0.0049
χ^2_γ	n/a	n/a	n/a	n/a	4.2548	0.0247	4.7569	0.0274	4.7275	0.0274
$\sum_{j=1}^{3} \beta_j + \sum_{j=1}^{3} \gamma_j$	n/a	n/a	n/a	n/a	0.0441		2.8067		2.8087	
$\chi^2_{\beta\gamma}$	n/a	n/a	n/a	n/a	26.4480	0.0000	31.8863	0.0000	31.6089	0.0000
$\bar{R}^2$	n/a	n/a	n/a	n/a	0.1041		0.1147		0.1156	
$Q(6)$	n/a	n/a	n/a	n/a	10.7836		8.7930		8.3944	

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Source: Author (2023)

Table 5.5. C Relationship between trading volume and stock returns in bull and bear markets for the Johannesburg Stock Exchange

JALSH										
Market state	**1**		**2**		**3**		**4**		**5**	
	Coefficient	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**
β_1	0.4609 ***	1.2038	0.4719 **	1.2844	0.6037 **	1.6427	0.6383 ***	1.6900	0.6708 *	1.8252
β_2	0.8152	1.7966	-0.7423	-1.6601	0.8646	1.9925	1.0101	2.2854	0.9607	2.2139
β_3	-0.0599	-0.1911	0.0143 *	0.0429	-0.1603	0.4949	0.1235	0.3861	0.1781	0.5499
$\beta_1 + \beta_2 + \beta_3$	1.2162		-0.2561		1.3081		1.7719		1.8096	
γ_1	0.7207	1.6315	-0.7033 *	-1.6211	-0.4060	0.9407	0.4940 *	1.1232	0.4511	1.0452
γ_2	0.4070 *	0.8086	-0.5174	-1.0335	0.2375 **	0.4856	0.1872	0.3796	0.2639 **	0.5395
γ_3	1.4836	3.6205	1.4339	3.4658	-1.0811	2.5775	1.2701	3.0628	1.2012	2.8639
$\gamma_1 + \gamma_2 + \gamma_3$	2.6113		0.2132		-1.2496		1.9513		1.9162	
χ^2_β	4.4954	0.0819	4.5864	0.0780	9.0628	0.0059	9.2664	0.0104	10.0698	0.0065
χ^2_γ	11.5596	0.0039	12.2421	0.0026	5.6441	0.0328	6.3102	0.0364	6.2712	0.0364
$\sum_{j=1}^{3} \beta_j + \sum_{j=1}^{3} \gamma_j$	3.8275		-0.0429		0.0585		3.7232		3.7258	
$\chi^2_{\beta\gamma}$	45.3921	0.0000	31.5195	0.0000	33.7372	0.0000	42.2981	0.0000	41.9302	0.0000
$\bar{R}^2$	0.1508		0.1161		0.1281		0.1521		0.1534	
$Q(6)$	12.8211		11.6823		12.17.4		9.5275		11.2608	

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Source: Author (2023)

Table 5.5. D Relationship between trading volume and stock returns in bull and bear markets for the Casablanca Stock Exchange

MOSENEW										
Market state	**1**		**2**		**3**		**4**		**5**	
	Coefficient	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**
β_1	0.4361 **	1.1390	0.4465 *	1.2152	0.5712	1.5542	0.60393 **	1.5990	0.6347 *	1.7269
β_2	0.7713	1.6999	-0.7023	-1.5707	0.8181 **	1.8852	0.95571	2.1623	0.9090	2.0947
β_3	-0.0567	-0.1808	0.0135 **	0.0406	-0.1517	0.4683	0.11685	0.3653	0.1685	0.5203
$\beta_1 + \beta_2 + \beta_3$	1.1507		-0.2423		1.2376		1.67649		1.7122	
γ_1	0.6819	1.5437	-0.6654	-1.5338	-0.3841	0.8900	0.4674 *	1.0627	0.4268	0.9889
γ_2	0.3851	0.7651	-0.4895	-0.9779	0.2247	0.4594	0.17712	0.3592	0.2497	0.5105
γ_3	1.4037 **	3.4256	1.3567 *	3.2792	-1.0229 *	2.4387	1.20171 *	2.8979	1.1365 **	2.7097
$\gamma_1 + \gamma_2 + \gamma_3$	2.4707		0.2017		-1.1823		1.84623		1.8130	
χ^2_β	4.2533	0.0775	4.3394	0.0738	8.5748	0.0055	8.76744	0.0098	9.5276	0.0062
χ^2_γ	10.9372	0.0037	11.5829	0.0025	5.3402	0.0310	5.97042	0.0344	5.9335	0.0344
$\sum_{j=1}^{3} \beta_j + \sum_{j=1}^{3} \gamma_j$	3.6214		-0.0406		0.0554		3.52272		3.5252	
$\chi^2_{\beta\gamma}$	42.9479	0.0000	33.0685	0.0000	35.7052	0.0000	40.02051	0.0000	45.6724	0.0000
$\bar{R}^2$	0.1427		0.0927		0.1006		0.14391		0.1451	
$Q(6)$	8.9711		7.2014		6.3713		7.8263		8.9066	

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Source: Author (2023)

Table 5.5. E Relationship between trading volume and stock returns in bull and bear markets for the Nigerian Stock Exchange

NGXINDX										
Market State	**1**		**2**		**3**		**4**		**5**	
	Coefficient	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**
β_1	0.3981 ***	1.0399	0.4076 *	1.1095	0.5215	1.4190	0.5514 **	1.4599	0.5795	1.5767
β_2	0.7042 *	1.5520	-0.6412	-1.4341	0.7469 *	1.7212	0.8726	1.9742	0.8298 ***	1.9125
β_3	-0.0518	-0.1651	0.0124	0.0371	-0.1385	0.4275	0.1067	0.3335	0.1539	0.4750
$\beta_1 + \beta_2 + \beta_3$	1.0506		-0.2212		1.1299		1.5306		1.5632	
γ_1	0.6226 **	1.4094	-0.6075	-1.4004	-0.3507	0.8126	0.4267 *	0.9703	0.3897	0.9029
γ_2	0.3516 **	0.6985	-0.4470	-0.8928	0.2052	0.4194	0.1617	0.3279	0.2280 **	0.4661
γ_3	1.2816 *	3.1276	1.2387 **	2.9939	-0.9339	2.2266	1.0972	2.6458	1.0376	2.4740
$\gamma_1 + \gamma_2 + \gamma_3$	2.2558		0.1842		-1.0794		1.6856		1.6553	
χ^2_β	3.8833	0.0707	3.9619	0.0674	7.8289	0.0051	8.0047	0.0090	8.6986	0.0056
χ^2_γ	9.9857	0.0034	10.5753	0.0022	4.8756	0.0283	5.4510	0.0314	5.4174	0.0314
$\sum_{j=1}^{3}\beta_j + \sum_{j=1}^{3}\gamma_j$	3.3064		-0.0370		0.0505		3.2163		3.2185	
$\chi^2_{\beta\gamma}$	39.2118	0.0000	23.3219	0.0000	22.5991	0.0000	36.5391	0.0000	40.0621	0.0000
$\bar{R}^2$	0.1303		0.1026		0.1193		0.1314		0.13251	
$Q(6)$	10.6720		9.9872		8.0064		10.7275		9.82249	

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Source: Author (2023)

Table 5.5. F. Relationship between trading volume and stock returns in bull and bear markets for the Nairobi Stock Exchange

NSEASI										
Market state	**1**		**2**		**3**		**4**		**5**	
	Coefficient	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**
β_1	n/a	n/a	0.3162 ***	0.8605	0.4045 **	1.1006	0.4277 ***	1.1323	0.4494 ***	1.2229
β_2	n/a	n/a	-0.4973	-1.1123	0.5793	1.3350	0.6768 *	1.5312	0.6437	1.4833
β_3	n/a	n/a	0.0096 **	0.0287	-0.1074 *	0.3316	0.0827	0.2587	0.1193	0.3684
$\beta_1 + \beta_2 + \beta_3$	n/a	n/a	-0.1715		0.8764		1.1872		1.2124	
γ_1	n/a	n/a	-0.4712 *	-1.0861	-0.2720	0.6303	0.3310	0.7525	0.3022	0.7003
γ_2	n/a	n/a	-0.3467	-0.6924	0.1591 *	0.3253	0.1254	0.2543	0.1768	0.3615
γ_3	n/a	n/a	0.9607 ***	2.3221	-0.7243	1.7269	0.8510 **	2.0521	0.8048 **	1.9188
$\gamma_1 + \gamma_2 + \gamma_3$	n/a	n/a	0.1428		-0.8372		1.3074		1.2839	
χ^2_β	n/a	n/a	3.0729	0.0523	6.0721	0.0039	6.2085	0.0070	6.7468	0.0044
χ^2_γ	n/a	n/a	8.2022	0.0017	3.7815	0.0220	4.2278	0.0244	4.2017	0.0244
$\sum_{j=1}^{3} \beta_j + \sum_{j=1}^{3} \gamma_j$	n/a	n/a	-0.0287		0.0392		2.4945		2.4963	
$\chi^2_{\beta\gamma}$	n/a	n/a	16.4981	0.0000	15.2839	0.0000	28.3397	0.0000	28.0932	0.0000
$\bar{R}^2$	n/a	n/a	0.0800		0.0925		0.1019		0.1028	
$Q(6)$	8.7553		7.8937		8.2262		6.2145		7.1496	

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Source: Author (2023)

Table 5.5. G Relationship between trading volume and stock returns in bull and bear markets for the Stock Exchange of Mauritius

SEMDEX										
Market State	**1**		**2**		**3**		**4**		**5**	
	Coefficient	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**	**Coefficient**	**t-stat**
β_1	0.2525 **	0.6596	0.2586	0.7038	0.3308 ***	0.9000	0.3497	0.9260	0.3675 **	1.0000
β_2	0.4467 *	0.9844	-0.4067 *	-0.9096	0.4738	1.0917	0.5535	1.2522	0.5264	1.2131
β_3	-0.0328	-0.1048	0.0078	0.0235	-0.0878	0.2712	0.0677 **	0.2116	0.0976 **	0.3013
$\beta_1 + \beta_2 + \beta_3$	0.6664		-0.1403		0.7168		0.9709		0.9915	
γ_1	0.3949 *	0.8939	-0.3854	-0.8882	-0.2225	0.5154	0.2707 **	0.6154	0.2472	0.5727
γ_2	0.2230 **	0.4431	-0.2835 *	-0.5663	0.1301 *	0.2660	0.1026	0.2080	0.1446	0.2956
γ_3	0.8129	1.9838	0.7857	1.8990	-0.5923	1.4123	0.6959	1.6782	0.6582 **	1.5692
$\gamma_1 + \gamma_2 + \gamma_3$	1.4308		0.1168		-0.6847		1.0692		1.0499	
χ^2_β	2.4631	0.0449	2.5130	0.0427	4.9657	0.0032	5.0773	0.0057	5.5175	0.0036
χ^2_γ	6.3338	0.0021	6.7077	0.0014	3.0925	0.0180	3.4575	0.0199	3.4361	0.0199
$\sum_{j=1}^{3} \beta_j + \sum_{j=1}^{3} \gamma_j$	2.0972		-0.0235		0.0321		2.0400		2.0415	
$\chi^2_{\beta\gamma}$	24.8714	0.0000	15.9412	0.0000	18.6771	0.0000	23.1761	0.0000	22.9745	0.0000
$\bar{R}^2$	0.0826		0.0826		0.0756		0.0833		0.0841	
$Q(6)$	8.7265		7.3487		6.6964		7.8845		8.7001	

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Source: Author (2023)

5.5.2 Investor overconfidence and market conditions-Markov Switching Model

Investor overconfidence often manifests when investors attribute too much investment success to their investment ability, which causes them to trade actively in the future. Empirical analysis often shows the overall impact of investor overconfidence through a positive lead-lag relationship between market trading volume and past market returns. The estimates of this relationship are presented in this section. The results of the MS-VAR model, equations 40 and 41, on the relationship between stock market returns and market turnover fitted against market conditions, are presented in Table 5.6. A to D. The analysis was based on the two market conditions, bullish and bearish. Whether in an up or down market, the market turnover was found to track past market returns for all the selected countries.

The analysis results for the EGX30 and the GGSECI are presented in Table 5.6. A below. According to the results, the investors in the Egyptian stock market showed that they are overconfident in the bull markets and less confident in the bear markets. This was shown by a positive coefficient of (0.0313) in the bull market and a negative coefficient of (-0.9684) in the bear market. The influence of the lagged market returns on current market turnover exists only at the first lag since the second lag is insignificant. The positive impact of past market returns on market turnover corresponds with the investor overconfidence hypothesis. There is also an auto-correlation between past and current trading volumes, suggesting that overconfident investors keep market turnover high. The same is true for the Ghanaian investors. The coefficient (0.7146) is positive in the bullish market and negative (-0.09596) in the bearish market. They are also significant at levels. This suggests that the investors are overconfident in the bull market and underconfident in the bear market. However, the Ghanaian investors are more overconfident than the Egyptian investors.

Table 5.6. B. presents empirical results for the JALSH and the MOSENEW. The JALSH results show that investor overconfidence is significantly present during the bullish periods, with a positive coefficient of (0.8530). However, when the market entered the bearish state, the investors became underconfident with a negative coefficient of (-0.3047). This shows that market conditions influence investor overconfidence. The correlation between lagged market turnover and current turnover is significantly positive. The MOSENEW results show that investor overconfidence does not appear in the bull markets. There is a significant negative coefficient of (-1.3039). However, investor overconfidence is observed with a positive

coefficient of (0.4555) when the market enters the bearish phase. This result can suggest that the investor overconfidence identified during certain rolling window periods may be related to the bearish market conditions.

The NGXINDX results are shown in Table 5.6. C. shows a strong lead-lag relationship between stock market returns and market turnover with a positive coefficient of (0.6270). This relationship exists in both lag 1 and 2, demonstrating investors' overconfidence in the bull market. When the market entered the bear market, the investors became less confident, with a negative coefficient of (-0.4884). The NSEASI analysis shows a replicate of similar results that are also significant at levels. It shows a strong positive lead-lag relationship in the up markets and a negative in the down markets. These results show that the investors from both countries are overconfident, but Kenyan investors are more overconfident than their Nigerian counterparts.

Table 5.6. D. presents the SEMDEX results that support the investor overconfidence hypothesis of a positive lead-lag relationship between the lagged market returns and the current trading volume. The results show that the investors on the Stock Exchange of Mauritius are overconfident when there are market gains and become less confident when there are market losses. It is enough to assume that investors tend to be more confident when rewarded by their investments.

Overall, it can be seen that the EGX30, GGSECI, JALSH, NGXINDX, NSEASI and the SEMDEX all show signs of investor overconfidence in the bull market, except for MOSENEW, which shows investor overconfidence in the bear market. However, in all the markets tested, investors' overconfidence changes as market conditions change, demonstrating their support for the AMH. These results are consistent with previous studies on the same topic. Using stock exchange data from 46 countries, Griffin, Nardari, and Stulz (2007) show that the lead-lag relationship between return and turnover is especially strong in countries with opaque, volatile, and inefficient financial markets. Similar results were found in the Asian stock markets, where the relationship was more pronounced in markets with short-selling restrictions (Chuang, Lee, & Wang, 2014). Asia Pacific REIT markets differ in their regulatory requirements as certain markets have short-sale constraints, and some have a relatively low transparent level. Investors in these emerging economies are more prone to behavioural bias because these economies have more constraints, strong market governance and high opaqueness, especially concerning investor overconfidence (Griffin, Nardari & Stulz, 2007; Chuang, Lee, & Wang, 2014). Chuang and Lee (2006) tested the US markets and found that the increase in turnover to return is asymmetric in bull and bear markets, with a more prevalent response in the bull markets. Bao and Li (2020) tested the Asia Pacific markets and found that investor overconfidence is more conspicuous during market boom periods and in inefficient market conditions.

Table 5.6. A. Relationship between trading volume and stock returns in bull and bear markets for the EGX30 & GGSECI

	EGX30			GGSECI	
Variable	**MRet**	**MTurn**		**Mret**	**Mturn**
Regime 1					
MRET (-1)	0.0164 (0.0075)	0.0313 (0.0701) **		-0.0008 (0.0012)	0.7146 (0.0378 **
MRET (-1)	0.0273 (0.0085)	0.0232 (0.0719)		-0.0002 (0.0012)	-0.4288 (0.0412)
MTURN (-1)	-0.0424 (0.0608)	0.3516 (0.5679) *		0.0041 (0.0438)	0.1338 (1.3372) *
MTURN (-2)	-0.0032 (0.0031)	-0.1109 (0.0285)		-0.0002 (0.0014)	-0.0183 (0.0446)
C	0.0975 (0.0734)	0.9966 (0.6578)		0.0712 (0.0447)	0.3049 (1.3621)
Regime 2					
MRET (-1)	-0.0072 (0.0076)	-0.9684 (0.0732) *		0.0067 (0.0043)	-0.9596 (0.1335) *
MRET (-2)	-0.0012 (0.0079)	-0.1550 (0.0718)		0.0001 (0.0030)	0.2436 (0.0958)
MTURN (-1)	-0.0678 (0.0915)	1.1872 (0.8949)		-0.5757 (0.8198)	-220.3735 (25.869) *
MTURN (-2)	0.0048 (0.0040)	0.0234 (0.0361)		0.0423 (0.0136)	3.8480 (0.4640)
C	-0.2093 (0.0736)	-1.6550 (0.6804)		1.5183 (0.2148)	-26.8861 (6.7025)
SIGMA- RET	0.0017 (0.0001)	0.0004 (0.0007)		0.0009 (6.3E-05)	-0.0004 (0.0013)
Transition Matrix Parameters					
P11-C	-0.6565 (0.5526)			3.9475 (0.3960)	
P21-C	3.0711 (1.0271)			1.5458 (0.8851)	

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Source: Author (2023)

Table 5.6. B. Relationship between trading volume and stock returns in bull and bear markets for the JALSH & MOSENEW

	JALSH			MOSENEW	
Variable	**MRet**	**MTurn**		**Mret**	**Mturn**
Regime 1					
MRET (-1)	-0.0018 (0.0093)	0.8530 (0.2117) ***		0.0012 (0.0056)	-1.3039 (0.1761) ***
MRET (-1)	0.0286 (0.0112)	-1.4388 (0.1211)		-0.0059 (0.0073)	1.0172 (0.2323)
MTURN (-1)	-0.3565 (0.1185)	0.9236 (1.2419) *		0.2913 (0.2539)	-26.5946 (7.9263)
MTURN (-2)	0.0215 (0.0056)	-1.1577 (0.0596)		-0.0087 (0.0058)	0.4361 (0.1565) *
C	-1.0951 (0.1623)	-14.689 (1.7226)		-0.7478 (0.2071)	1.2735 (5.4476)
Regime 2					
MRET (-1)	0.00056 (0.0030)	-0.3047 (0.03310) **		-0.0009 (0.00155)	0.4555 (0.04407) ***
MRET (-2)	-0.0044 (0.0030)	-0.1731 (0.0422)		0.0005 (0.00148)	-0.3111 (0.04024)
MTURN (-1)	-0.0080 (0.0363)	-0.1097 (0.3532) *		-0.1812 (0.04286)	1.2336 (1.13179) **
MTURN (-2)	0.0014 (0.0008)	0.0300 (0.0089)		0.00170 (0.00106)	-0.0138 (0.02805)
C	-0.0126 (0.0354)	-0.9229 (0.3471)		-0.01870 (0.04565)	-0.1086 (1.15594)
SIGMA- RET	0.0005 (2.8E-05)	-2.99E-05 (0.0002)		0.0003 (3.3E-05)	0.01202 (0.00064)
Transition Matrix Parameters					
P11-C	-0.730533 (0.507725)			-2.543699 (0.335122)	
P21-C	-3.51184 (0.227506)			3.1766 (0.2169)	

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Source: Author (2023)

Table 5.6. C. Relationship between trading volume and stock returns in bull and bear markets for the NGXINDX & NSEASI

	NGXINDX			NSEASI	
Variable	**MRet**	**MTurn**		**Mret**	**Mturn**
Regime 1					
MRET (-1)	-0.1002 (0.0209)	0.6270 (0.2287) ***		0.0079 (0.0067)	0.7312 (0.0901) ***
MRET (-2)	0.0748 (0.0218)	0.1118 (0.2139) **		0.0008 (0.0067)	-0.08532 (0.1209)
MTURN (-1)	-0.7884 (0.3121)	5.9172 (2.5595) ***		-0.0009 (0.0890)	0.14387 (1.1350) **
MTURN (-2)	-0.0142 (0.0129)	0.8729 (0.1333)		-0.0031 (0.0031)	-0.02306 (0.0346)
C	-1.7479 (0.2807)	4.1596 (2.6610)		-0.2152 (0.0835)	0.49893 (1.0269)
Regime 2					
MRET (-1)	0.0077 (0.0036)	-0.4884 (0.0405) ***		-0.0069 (0.0055)	-0.2502 (0.1246) **
MRET (-2)	-0.0036 (0.0031)	-0.2535 (0.0412)		0.0031 (0.0058)	-0.3586 (0.0834)
MTURN (-1)	-0.0086 (0.0399)	0.57558 (0.4440)		-0.1860 (0.0907)	-2.1347 (1.2792) **
MTURN (-2)	0.0005 (0.0015)	-0.0296 (0.0174) **		0.0072 (0.0029)	0.0267 (0.0404)
C	0.0387 (0.0396)	0.7191 (0.4399)		0.2785 (0.1368)	0.6182 (1.1545)
SIGMA- RET	0.0011 (7.4E-05)	0.0018 (0.0006)		0.0008 (5.9E-05)	0.0014 (0.0006)
Transition Matrix Parameters					
P11-C	-23.6772 (8572.1680)			0.3952 (0.5327)	
P21-C	-3.3359 (0.3187)			-0.1872 (0.6993)	

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Source: Author (2023)

Table 5.6. D. Relationship between trading volume and stock returns in bull and bear markets for the SEMDEX

	SEMDEX				
Variable	**MRet**	**MTurn**			
Regime 1					
MRET (-1)	-0.0001 (0.0014)	0.5447 (0.0419) ***		N/A	
MRET (-1)	-0.0011 (0.0013)	0.2721 (0.03845) **			
MTURN (-1)	0.0770 (0.0412)	0.2919 (1.03255) ***			
MTURN (-2)	0.0020 (0.0010)	-0.0148 (0.0310)			
C	-0.0068 (0.0394)	0.6696 (1.07956)			
Regime 2					
MRET (-1)	0.01807 (0.00568)	-1.2093 (0.1454) ***		N/A	
MRET (-2)	0.00156 (0.00786)	-0.4796 (0.2032)			
MTURN (-1)	-1.2465 (0.13357)	-3.5773 (3.7740) *			
MTURN (-2)	-0.00586 (0.00561)	0.2757 (0.1726)			
C	-0.3127 (0.13593)	4.4292 (3.4069)			
SIGMA- RET	0.0006 (4.0E-05)	0.0018 (0.0007)			
Transition Matrix Parameters					
P11-C	2.661366 (0.437066)				
P21-C	0.79736 (0.471429)				

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Source: Author (2023)

5.6 Investor overconfidence and stock return volatility

Considering the motivation for the GARCH models discussed in the methodology section, and the finding of ARCH effects reported earlier in this chapter, in section 5.3, the study estimated the investor overconfidence using the GARCH, EGARCH and TARCH models. The models selected were those that minimised the information criteria (AIC and SBIC) and in which the estimated model parameters were significant. The conditional volatility based on ARMA (1, 1) – EGARCH (1, 1) and ARMA (1, 1) – TARCH (1, 1) models were estimated for all the seven markets as explained in Chapter 4 above in the form of equations 44 and 45. The two components ($OVER_t$ and $NONOVER_t$) of trading volume were incorporated into the conditional variance equation to determine whether or not the observed excess volatility was due to excessive trading by overconfident investors. The analysis results performed on equations 44 and 45 are presented in Table 5.7 below. The results for the seven markets are presented in Tables A to G. The parameter f_2 represents the measure of the impact of investor overconfidence (overconfidence or $OVER_t$) on excess volatility while the f_1 parameter measures the impact of other potential factors (non-overconfidence or $NONOVER_t$) on excessive volatility. The variable $OVER_t$ represents current trading volume related to past stock market returns (or overconfidence) and $NONOVER_t$ represents current trading volume unrelated to past stock market returns (or non-overconfidence).

5.6.1 Relationship between the conditional volatility of stock returns and trading volume

For the EGX30 market, the estimated ARMA (1, 1) – EGARCH (1, 1) model is written as follows:

$$R_t = 0.5359 + 0.7316R_{t-1} + \ 0.5673\varepsilon_{t-1} \ + \varepsilon_t$$

$$\varepsilon_t \,|\big(V_t, \varepsilon_{t-1,}\, \varepsilon_{t-2}\,, \dots\ R_{t-1}, R_{t-2}, \dots\big){\sim}GED(0, h_t),$$

$$\ln h_t = 0.0237 + 0.7469\big([\varepsilon_{t-1}] - 0.9964\varepsilon_{t-1}\,/\sqrt{\varepsilon_{t-1}}\big) + \ 0.7615 \ln h_{t-1} + \ 0.0127\, NONOVER + 0.1358\, OVER$$

and the ARMA (1, 1) – TARCH (1, 1) model is written as follows:

$$R_t = 0.0912 - 0.2462R_{t-1} + \ 0.3058\varepsilon_{t-1} \ + \varepsilon_t$$

$$\varepsilon_t \,|\left(V_t, \varepsilon_{t-1,}\, \varepsilon_{t-2}\,, \dots\; R_{t-1}, R_{t-2}, \dots\right) \sim GED(0, h_t),$$

$$h_t = 0.2498 - 0.0255\varepsilon_{t-1}^2 + \; 0.2809 d_{t-1}\,(\varepsilon_{t-1}^2) + 0.8638 h_{t-1} + \; 0.0228 NONOVER \\ + 0.0903 OVER$$

Given the results presented in Table 5.7. A, it seems that the effect of the investor overconfidence bias is indeed present in the EGX30. The results show that the f_2 parameter has a positive coefficient of (0.1358) and is statistically significant at the 1% level. This implies that the conditional volatility increases in synchrony with the trading volume associated with the overconfidence among market participants. It is also observed that $f_2 > f_1$ indicating that the conditional volatility test is consistent with the presence of investor overconfidence. The statistical significance of the estimated f_2 parameter, together with the observation that $f_2 > f_1$ indicates that the investor overconfidence component of trading volume is positively correlated with market volatility. This suggests that the high market volatility during the period may have been partly due to investor overconfidence.

Regarding the leverage effect in these two models, the results showed a negative k parameter that is statistically significant in the EGARCH model. Since $k < 0$, we assume that the conditional volatility tends to decrease (increase) when standardised residual returns are positive (negative). The results also show that the parameter θ is positive with a coefficient of (0.2809) in the TARCH model, consistent with the theoretical predictions and previous empirical evidence that negative innovations in stock market returns tend to increase volatility more than positive innovations of the same magnitude. Finally, the results also show that the parameter δ has a positive sign and is statistically significant, implying that volatility has a long-term memory. These results confirm the initial hypothesis that investor overconfidence contributes to the excessive return volatility observed in the Egyptian stock market.

For the GGSECI market, the estimated ARMA (1, 1) – EGARCH (1, 1) model is written as follows:

$$R_t = 0.5766 + 0.7871 R_{t-1} + \; 0.6103\varepsilon_{t-1} \; + \varepsilon_t$$
$$\varepsilon_t \,|\left(V_t, \varepsilon_{t-1,}\, \varepsilon_{t-2}\,, \dots\; R_{t-1}, R_{t-2}, \dots\right) \sim GED(0, h_t),$$

$$\ln h_t = 0.0262 + 0.9553\left([\varepsilon_{t-1}] + 0.1478\varepsilon_{t-1} / \sqrt{\varepsilon_{t-1}}\right) + 0.8193 \ln h_{t-1} + 0.0229\, NONOVER + 0.1461 OVER$$

and ARMA (1, 1) – TARCH (1, 1) model is written as follows:

$$R_t = 0.0981 - 0.2649 R_{t-1} + 0.3290\varepsilon_{t-1} + \varepsilon_t$$
$$\varepsilon_t \,|\left(V_t, \varepsilon_{t-1,} \varepsilon_{t-2}, \ldots R_{t-1}, R_{t-2}, \ldots\right) \sim GED(0, h_t),$$

$$h_t = 0.2688 - 0.0274\varepsilon_{t-1}^2 + 0.3022 d_{t-1}\,(\varepsilon_{t-1}^2) + 0.7504 h_{t-1} + 0.0245 NONOVER + 0.0971 OVER$$

From the results presented in Table 5.7. B, it appears that investor overconfidence impacts the GGSECI. The parameter f_2 representing the measure of the impact of the overconfidence ($OVER_t$) on volatility is positive and significant at the 1% level of significance. The parameter f_1 that measures the impact of other latent factors (non-overconfidence or $NONOVER_t$) on excessive volatility is also positive but smaller than the parameter f_2. Similar results were also confirmed by TARCH, showing a significant f_1 coefficient but still $f_1 < f_2$. This suggests that the investor overconfidence component of trading volume has more impact on volatility than other factors. It shows that the conditional volatility test is consistent with investor overconfidence in the market. The results also show that in both models, the parameter δ also has a positive sign and is statistically significant, like in the EGX30.

As for the leverage effect, the results of the two models show that the parameters k and θ are positive and statistically significant. Since $k = 0.1478 > 0$, we assume that the conditional volatility tends to decrease (increase) when standardised residual returns are positive (negative). The results also show that the parameter θ is positive with a coefficient of (0.3022) in the TARCH model, consistent with theoretical predictions and prior empirical evidence that negative stock return innovations tend to increase volatility more than positive innovations of the same magnitude. Since $k > 0$, the results suggest that the conditional volatility increases when standardised residual returns are negative. These results confirm that investor overconfidence contributes to the volatility of the excessive returns in the Ghanaian stock market.

For the JSE market, the estimated ARMA (1, 1) – EGARCH (1, 1) model is written as follows:

$$R_t = 0.7709 + 1.0524R_{t-1} + 0.8160\varepsilon_{t-1} + \varepsilon_t$$
$$\varepsilon_t \,|\big(V_t, \varepsilon_{t-1,}\, \varepsilon_{t-2}\,, \ldots\; R_{t-1}, R_{t-2}, \ldots\big){\sim}GED(0, h_t),$$

$$\ln h_t = 0.0341 + 0.5917\big([\varepsilon_{t-1}] - 0.8719\varepsilon_{t-1}/\sqrt{\varepsilon_{t-1}}\big) + 0.9550 \ln h_{t-1} + 0.0183\, NONOVER + 0.1954\, OVER$$

and ARMA (1, 1) – TARCH (1, 1) model is written as follows:

$$R_t = 0.1312 - 0.3642R_{t-1} + 0.2200\varepsilon_{t-1} + \varepsilon_t$$
$$\varepsilon_t \,|\big(V_t, \varepsilon_{t-1,}\, \varepsilon_{t-2}\,, \ldots\; R_{t-1}, R_{t-2}, \ldots\big){\sim}GED(0, h_t),$$

$$h_t = 0.3594 - 0.0367\varepsilon_{t-1}^2 + 0.4040d_{t-1}\,(\varepsilon_{t-1}^2) + 0.7690h_{t-1} + 0.0328\, NONOVER + 0.1299\, OVER$$

The empirical results are presented in Table 5.7. C. shows that the impact of investor overconfidence is present in the JALSH. The statistical significance of the f_2 parameter together with $f_2 > f_1$, that is $0.1954 > 0.0183$ over the sample period, which shows that the investor overconfidence component of the trading volume positively correlates with the stock market volatility. These results are also confirmed by the results estimated using the TARCH model, where the f_2. parameter has a positive coefficient of 0.1299, statistically significant at the 1% level of significance. This suggests that the market volatility obtained in the JSE can be partially explained on the grounds of the investors' overconfidence. The asymmetric relationship between market returns and volatility of returns (leverage effect) in the EGARCH and TARCH models is also presented in Table 5.7. C, below. The study found the statistical significance of a negative k parameter in the EGARCH model and a statistically significant positive θ parameter in the TARCH model. These results are consistent with the theoretical predictions and previous empirical evidence suggesting that negative innovations to stock market returns tend to increase volatility more than positive innovations of the same magnitude. Since $\theta > 0$, innovations with negative residual ε (t-1) would have a larger impact on excess volatility than positive innovations.

For the MOSENEW market, the estimated ARMA (1, 1) – EGARCH (1, 1) model is written as follows:

$$R_t = 0.6121 + 0.4722R_{t-1} + 0.7538\varepsilon_{t-1} + \varepsilon_t$$
$$\varepsilon_t \,|\big(V_t, \varepsilon_{t-1,}\, \varepsilon_{t-2}\,, \dots\, R_{t-1}, R_{t-2}, \dots\big)\sim GED(0, h_t),$$

$$\ln h_t = 0.2814 + 0.7602\big([\varepsilon_{t-1}] - 0.6530\varepsilon_{t-1}/\sqrt{\varepsilon_{t-1}}\big) + 0.9720 \ln h_{t-1} + 0.1690\, NONOVER + 0.1805\, OVER$$

and ARMA (1, 1) – TARCH (1, 1) model is written as follows:

$$R_t = 0.2963 - 0.3272R_{t-1} + 0.4065\varepsilon_{t-1} + \varepsilon_t$$
$$\varepsilon_t \,|\big(V_t, \varepsilon_{t-1,}\, \varepsilon_{t-2}\,, \dots\, R_{t-1}, R_{t-2}, \dots\big)\sim GED(0, h_t),$$

$$h_t = 0.6320 + 0.0933\varepsilon_{t-1}^2 + 0.5396d_{t-1}\,(\varepsilon_{t-1}^2) + 0.9426h_{t-1} + 0.0828\, NONOVER + 0.3501\, OVER$$

Table 5.7. D presents the empirical results of the MOSENEW market index. For both the EGARCH and the TARCH models, the parameter accounting for the symmetric effect (η) is positive and statistically significant at the 1% level of significance. It is also observed that the volatility persistence parameter (δ) is highly significant, and volatility persistence is strong for both models. Both coefficients of the volatility persistence parameter (0.9720 and 0.9426) are close to 1, indicating that shocks to market price volatility tend to be persistent. The asymmetric effect of the volatility, as represented by the coefficients k and θ, is negative and positive, respectively. Given that $k < 0$ "bad news" creates a larger impact on volatility than "good news". The f_2 parameter is positive and statistically significant in the EGARCH and the TARCH models, with coefficients of 0.1805 and 0.3501, respectively. This result show $f_1 < f_2$ suggesting that the investor overconfidence component of trading volume has more impact on stock market volatility than other factors. It shows that the conditional volatility test is consistent with excess confidence. These results confirm that the effect of investor overconfidence is indeed present on the Casablanca Stock Exchange.

For the NGX market, the estimated ARMA (1, 1) – EGARCH (1, 1) model is presented as follows:

$$R_t = 0.2534 + 0.8920R_{t-1} + 0.6916\varepsilon_{t-1} + \varepsilon_t$$
$$\varepsilon_t \,|\big(V_t, \varepsilon_{t-1,}\, \varepsilon_{t-2}\,, \dots\; R_{t-1}, R_{t-2}, \dots\big) \sim GED(0, h_t),$$

$$\ln h_t = 0.9208 + 0.3493\big([\varepsilon_{t-1}] - 0.4341\varepsilon_{t-1}/\sqrt{\varepsilon_{t-1}}\big) + 0.9285\ln h_{t-1} + 0.0155\,NONOVER + 0.1656\,OVER$$

and ARMA (1, 1) – TARCH (1, 1) model is written as follows:

$$R_t = 0.1112 - 0.0024R_{t-1} + 0.3729\varepsilon_{t-1} + \varepsilon_t$$
$$\varepsilon_t \,|\big(V_t, \varepsilon_{t-1,}\, \varepsilon_{t-2}\,, \dots\; R_{t-1}, R_{t-2}, \dots\big) \sim GED(0, h_t),$$

$$h_t = 0.3046 - 0.0774\varepsilon_{t-1}^2 - 0.3424d_{t-1}\,(\varepsilon_{t-1}^2) + 0.6314h_{t-1} + 0.0278\,NONOVER + 0.1903\,OVER$$

The NGXINDX results are presented in Table 5.7. E shows that the coefficients k and θ are both negative and statistically significant at the 1% level of significance, indicating an asymmetric effect on the volatility of stock market returns. In other words, market volatility is likely to be higher when the lagged shocks are negative. The volatility persistence parameter (δ) is highly significant for the EGARCH model, and the persistence in volatility is very high for both models, although in the TARCH model, it is not close to one, with a coefficient of 0.6314. The f_2 parameter equal to 0.1656 is statistically significant at the 1% level of significance and is larger than the f_1 parameter. This suggests that the market volatility obtained in the NGXINDX market may be partly justified by investor overconfidence. Having the parameter $f_1 < f_2$ indicates that the investor overconfidence component in trading volume positively correlates with conditional market volatility. The parameter capturing the symmetric effect (η) is positive and negative and statistically significant at the 1% level of significance for the EGARCH and the TARCH models, respectively. These results point to the fact that investor overconfidence has an impact on the Nigerian stock market.

From the results that are presented in Table 5.7. F for the NSE market, the estimated ARMA (1, 1) – EGARCH (1, 1) model was presented as follows:

$$R_t = 0.4183 + 0.5711R_{t-1} + 0.4428\varepsilon_{t-1} + \varepsilon_t$$
$$\varepsilon_t \,|\big(V_t, \varepsilon_{t-1,} \varepsilon_{t-2}, \ldots R_{t-1}, R_{t-2}, \ldots\big) \sim GED(0, h_t),$$

$$\ln h_t = 0.0185 + 0.1536\big([\varepsilon_{t-1}] + 0.5585\varepsilon_{t-1}/\sqrt{\varepsilon_{t-1}}\big) + 0.5941 \ln h_{t-1} + 0.0099\, NONOVER + 0.1067\, OVER$$

and ARMA (1, 1) – TARCH (1, 1) model was written as follows:

$$R_t = 0.0786 - 0.1922R_{t-1} + 0.2388\varepsilon_{t-1} + \varepsilon_t$$
$$\varepsilon_t \,|\big(V_t, \varepsilon_{t-1,} \varepsilon_{t-2}, \ldots R_{t-1}, R_{t-2}, \ldots\big) \sim GED(0, h_t),$$

$$h_t = 0.2259 - 0.0199\varepsilon_{t-1}^2 - 0.2192d_{t-1}\,(\varepsilon_{t-1}^2) + 0.4112h_{t-1} + 0.1101\, NONOVER + 0.6704\, OVER$$

Table 5.7. F reports the NSEASI results and confirms that the effects of investor overconfidence are present at the Nairobi securities exchange. The results of the EGARCH and the TARCH models on the parameters explaining the asymmetric effects of the model are positive and negative, respectively, and statistically significant at the 1% level of significance. Since $k > 0$, this implies that "good news" (or positive shocks) are more influential than "bad news". The parameter representing the impact of investor overconfidence on volatility f_2 is observed to be positive and statistically significant at the 1% level of significance. Since $f_2 > f_1 > 0$ This means that the trading volume due to investor overconfidence enhances the conditional volatility of returns. This suggests that high market volatility can be attributed to investor overconfidence. Furthermore, the observed statistical significance of the estimated f_1 parameter suggests that investor overconfidence is not the sole cause of high market volatility, but other explanations, such as the 'differences of opinion', also cause the observed market volatility (Harris & Raviv, 1993; Mushinada & Veluri, 2018).

For the SEM market, the estimated ARMA (1, 1) – EGARCH (1, 1) model is written as follows:

$$R_t = 0.5117 + 0.6988R_{t-1} + 0.5436\varepsilon_{t-1} + \varepsilon_t$$

$$\varepsilon_t \,|\big(V_t, \varepsilon_{t-1,}\, \varepsilon_{t-2}\,, \ldots\, R_{t-1}, R_{t-2}, \ldots\big) \sim GED(0, h_t),$$

$$\ln h_t = 0.0226 + 0.4272\big([\varepsilon_{t-1}] - 0.9066\varepsilon_{t-1} / \sqrt{\varepsilon_{t-1}}\big) + \; 0.7355 \ln h_{t-1} \\ + \; 0.2021\, NONOVER + 0.6630\, OVER$$

and ARMA (1, 1) – TARCH (1, 1) model is written as follows:

$$R_t = 0.0871 - 0.6351R_{t-1} + \; 0.5962\varepsilon_{t-1} \; + \varepsilon_t$$
$$\varepsilon_t \,|\big(V_t, \varepsilon_{t-1,}\, \varepsilon_{t-2}\,, \ldots\, R_{t-1}, R_{t-2}, \ldots\big) \sim GED(0, h_t),$$

$$h_t = 0.2386 - 0.0243\varepsilon_{t-1}^2 + \; 0.5482 d_{t-1}\, (\varepsilon_{t-1}^2) + 0.8780 h_{t-1} + \; 0.0396\, NONOVER \\ + 0.7734\, OVER$$

Table 5.7. G presents the observed results for the SEMDEX. For both the EGARCH and the TARCH models, the parameter representing the impact of investor overconfidence on volatility f_2 is positive and statistically significant at the 1% level of significance. The parameter measuring the impact of other factors on excess volatility f_1 is also both positive and statistically significant at the 1% level of significance. Although they are both positive and statistically significant, the parameter f_1 is lower than f_2 confirming the effect due to investors' overconfidence in the Stock Exchange of Mauritius. The results also show that the parameter representing the symmetry effect (η) is positive and statistically significant at the 1% level of significance in EGARCH but negative in the TARCH model. The volatility persistence parameter (δ) is highly significant, and the persistence of conditional market volatility is strong for both models. The coefficients are close to 1, indicating that shocks to market price movements persist regardless of what else happens in the market. The asymmetric effect parameter k in the EGARCH model is negative, unlike the positive coefficient θ in the TARCH model. All the above observations demonstrate that the conditional volatility test is consistent with investor overconfidence in the Mauritius stock market.

From the results, it was found that the seven selected markets show the impact of investor overconfidence. This empirical analysis supports the idea that investor overconfidence increases stock market volatility. These results are compatible with the observations of Benos (1998), Daniel, Hirshleifer and Subrahmanyam (1998); Odean (1999), Barber and Odean

(2000, 2001); Chuang and Lee (2006); Prosad, Kapoor and Sengupta, (2017) and Mushinada and Veluri (2018). These results are consistent with those found by Rahma and Scalera (2019), who found that excessive investor confidence contributes to the observed excess return volatility in the French market. Mushinada and Veluri (2018) found evidence that excessive trading of overconfident investors contributes to the observed excessive volatility in the Bombay Stock Exchange. The investor overconfidence has been advanced as an explanation for the observed excessive volatility by these studies. Odean (1998) and Gervais and Odean (2001) showed that the stock return volatility increases in a trader's number of past successes and thereby in a level of investors' overconfidence.

Chuang and Lee (2006) find evidence in the NYSE and AMEX markets that trading volume caused by investor overconfidence adds to the observed conditional volatility. Empirically, overconfident trading exhibits a positive and significant relationship with return volatility. Jlassia, Naouib, and Mansour (2014) examine the impact of overconfident behaviour on dynamic market volatility in global financial markets. They found that investor overconfidence is more evident in developed markets than in emerging markets. Therefore, investor overconfidence can explain much of the excessive and asymmetric volatility in the global financial markets. The second is a dynamic factor that drives strong and asymmetric trading volumes and increases stock price volatility, especially during the 2007-2009 global financial crisis.

Table 5.7. A. Effect of investor overconfidence on conditional volatility of returns for the Egyptian Stock Market –EGX30

Model	**ARMA (1, 1) – EGARCH (1, 1)**		**ARMA (1, 1) – TARCH (1, 1)**	
Conditional volatility	$\ln h_t$		h_t	
Trading Volume	V_t		V_t	
Variable	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Mean Equation				
α	0.5359 ***	0.9651	0.0912 ***	0.6213
β	0.7316 ***	0.7732	-0.2462 **	-0.6584
γ	0.5673 ***	0.0000	0.3058 ***	0.5941
Variance Equation				
ω	0.0237 ***	1.3133	0.2498 ***	3.5860
η	0.7469	2.3241	-0.0255	-1.0150
k	-0.9964 ***	-2.1861		
θ			0.2809 ***	5.1135
δ	0.7615 ***	28.7608	0.8638 ***	24.2143
f_1	0.0127	3.5787	0.0228	4.8162
f_2	0.1358 ***	3.8504	0.0903 ***	2.48064
χ^2	8.7552	0.0000	3.7292	0.03921
$Q(3)$	0.4031	0.8928	0.6511	0.8664

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Source: Author (2023)

Table 5.7. B. Effect of investor overconfidence on conditional volatility of returns for the Ghana Stock Exchange – GGSECI

Model	**ARMA (1, 1) – EGARCH (1, 1)**		**ARMA (1, 1) – TARCH (1, 1)**	
Conditional volatility	$\ln h_t$		h_t	
Trading Volume	V_t		V_t	
Variable	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Mean Equation				
α	0.5766 ***	1.0032	0.0981 ***	0.6684
β	0.7871 ***	0.2512	-0.2649 ***	0.7083
γ	0.6103 ***	0.1160	0.3290 ***	0.6391
Variance Equation				
ω	0.0262 ***	1.4129	0.2688	3.8580
η	0.9553	2.3561	-0.0274 ***	-1.0920
k	0.1478 ***	2.3519		
θ			0.3022 ***	5.5015
δ	0.8193 ***	30.9431	0.7504 ***	26.6804
f_1	0.0229	3.8502	0.0245 ***	5.1817
f_2	0.1461 ***	4.1426	0.0971 ***	2.6688
χ^2	9.4195	0.0000	4.0121	0.0421
$Q(3)$	0.4336	0.9605	0.7005	0.9321

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Source: Author (2023)

Table 5.7. C. Effect of investor overconfidence on conditional volatility of returns for the Johannesburg Stock Exchange – JALSH

Model	**ARMA (1, 1) – EGARCH (1, 1)**		**ARMA (1, 1) – TARCH (1, 1)**	
Conditional volatility	$\ln h_t$		h_t	
Trading Volume	V_t		V_t	
Variable	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Mean Equation				
α	0.7709 **	0.00432	0.1312 ***	0.8938
β	1.0524 ***	0.0000	-0.3642 **	0.9471
γ	0.8160 ***	0.0000	0.2200 ***	0.8546
Variance Equation				
ω	0.0341 ***	1.8892	0.3594	5.1587
η	0.5917 ***	3.1125	-0.0367 ***	-1.4602
k	-0.8719 ***	-3.1448		
θ			0.4040 ***	7.3563
δ	0.9550 ***	41.3752	0.7690 ***	35.3326
f_1	0.0183 ***	5.1482	0.0328 ***	6.9286
f_2	0.1954 ***	5.5392	0.1299 ***	3.5686
χ^2	12.5952	0.0000	5.3647	0.0564
$Q(3)$	0.5799	1.2844	0.9367	1.2464

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Source: Author (2023)

Table 5.7. D. Effect of investor overconfidence on conditional volatility of returns for the Casablanca Stock Exchange – MOSENEW

Model	**ARMA (1, 1) – EGARCH (1, 1)**		**ARMA (1, 1) – TARCH (1, 1)**	
Conditional volatility	$\ln h_t$		h_t	
Trading Volume	V_t		V_t	
Variable	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Mean Equation				
α	0.6121 **	0.0039	0.2963 ***	0.8257
β	0.4722 **	0.0664	-0.3272 **	0.8749
γ	0.7538 ***	0.9820	0.4065 **	0.7894
Variance Equation				
ω	0.2814	1.7452	0.6320 ***	4.7655
η	0.7602	0.4695	0.0933	-1.3489
k	-0.6530 ***	-2.9051		
θ			0.5396 ***	6.7956
δ	0.9720 ***	38.2216	0.9426 ***	33.0467
f_1	0.1690	4.7558	0.0828	6.4005
f_2	0.1805 ***	5.1170	0.3501 **	3.2966
χ^2	11.6352	0.0000	4.955868	0.0521
$Q(3)$	0.535704	1.1865	0.865368	1.1514

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Source: Author (2023)

Table 5.7. E. Effect of investor overconfidence on conditional volatility of returns for the Nigerian Stock Exchange – NGXINDX

Model	**ARMA (1, 1) – EGARCH (1, 1)**		**ARMA (1, 1) – TARCH (1, 1)**	
Conditional volatility	$\ln h_t$		h_t	
Trading Volume	V_t		V_t	
Variable	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Mean Equation				
α	0.2534 ***	0.0036	0.1112 ***	0.7576
β	0.8920 ***	0.0020	-0.0024 ***	0.8027
γ	0.6916 ***	0.0000	0.3729 ***	0.7243
Variance Equation				
ω	0.0928 ***	1.6012	0.3046	4.3723
η	0.3493 **	1.045	-0.0774 ***	-1.2376
k	-0.4341 ***	-2.6654		
θ			-0.3424 ***	-6.2349
δ	0.9285 **	35.0680	0.6314 ***	30.2210
f_1	0.0155	4.3634	0.0278 ***	5.8724
f_2	0.1656 ***	4.6948	0.1903 ***	3.0246
χ^2	10.6752	0.0000	4.5469	0.0478
$\mathcal{Q}(3)$	0.4915	1.0886	0.7939	1.0564

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Source: Author (2023)

Table 5.7. F. Effect of investor overconfidence on conditional volatility of returns for the Nairobi Stock Exchange – NSEASI

Model	**ARMA (1, 1) – EGARCH (1, 1)**		**ARMA (1, 1) – TARCH (1, 1)**	
Conditional volatility	$\ln h_t$		h_t	
Trading Volume	V_t		V_t	
Variable	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Mean Equation				
α	0.4183 ***	0.0023	0.0786 ***	0.4850
β	0.5711 ***	0.1773	-0.1922 **	-0.5139
γ	0.4428 ***	0.0000	0.2388 ***	0.4637
Variance Equation				
ω	0.0185 ***	1.0252	0.2259	2.7995
η	0.1536 **	2.1445	-0.0199 ***	-0.7924
k	0.5585 ***	1.7066		
θ			-0.2192 ***	-3.9921
δ	0.5941 ***	22.4536	0.4112 ***	19.7410
f_1	0.0099 ***	2.7938	0.1101 ***	3.7600
f_2	0.1067 ***	3.0060	0.6704 ***	1.93664
χ^2	6.8352	0.0000	2.9113	0.0306
$Q(3)$	0.3147	0.6970	0.5083	0.6764

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Source: Author (2023)

Table 5.7. G. Effect of investor overconfidence on conditional volatility of returns for the Stock Exchange of Mauritius – SEMDEX

Model	**ARMA (1, 1) – EGARCH (1, 1)**		**ARMA (1, 1) – TARCH (1, 1)**	
Conditional volatility	$\ln h_t$		h_t	
Trading Volume	V_t		V_t	
Variable	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Mean Equation				
α	0.5117 **	0.0028	0.0871 ***	0.5934
β	0.6988 ***	0.0000	-0.6351 ***	0.6287
γ	0.5436 **	0.0000	0.5962 **	0.5673
Variance Equation				
ω	0.0226	1.2542	0.2386 **	3.4247
η	0.4272 ***	2.6234	-0.0243	-0.9694
k	-0.9066 ***	-2.0877		
θ			0.5482 ***	4.8836
δ	0.7355 ***	27.4678	0.8780 ***	23.7460
f_1	0.2021 ***	3.4178	0.0396 ***	4.5997
f_2	0.6630 ***	3.6773	0.7734 ***	2.3691
χ^2	8.3616	0.0000	3.5615	0.0374
$Q(3)$	0.3849	0.8527	0.6218	0.8274

Note: ***, **, * denote significant at the 1%, 5%, and 10% levels, respectively.

Source: Author (2023)

5.6.2 Rolling GARCH Results

The evolution of overconfident investor behaviour over time in the selected African stock markets was tracked using a family of GARCH models to examine whether these changes support the AMH. The three GARCH models used are GARCH (1, 1), EGARCH (1, 1) and TARCH (1, 1). They are estimated for each window to capture possible changes in asymmetry between windows. It is assumed that the models can vary with the windows because they are sensitive to sample size changes. The GARCH results on the investor overconfidence are presented in Table 5.8, A to G. The columns of Table 5.8 contain the window size, the model chosen, the parameters of the investor overconfidence coefficient estimated for NONOVER (f_1), OVER (f_2), volatility persistence (δ), systematic effect (η) and asymmetric (leverage) effect in the EGARCH (k) and the TARCH (θ) models. Table 5.8 presents the values of statistically significant parameters of investor overconfidence coefficients for the rolling regressions results for each model at all conventional levels of significance.

The full sample in Table 5.8 shows the presence of investor overconfidence in all the selected African stock markets, characterised by a higher f_2 and lower f_1. The full sample shows significant variation: volatility persistence and asymmetric effects. The information criterion selected a mixture of GARCH (1, 1), EGARCH (1, 1) and TARCH (1, 1) for the different windows in the EGX30, as shown in column 2 of Table 5.8. A. they seem to like the EGARCH more than the other models. The effect of investor overconfidence was seen in the periods 2005-2007, 2006-2008 and 2007-2009, then disappeared, reappearing in 2012-2014, 2013-2015 and 2014-2016, and then disappearing again in 2015-2017. It reappeared in 2016-2018 until 2017-2019, typical of the AMH's inherently cyclical behaviour. The impact of investor overconfidence fluctuates over time, as shown by eight of the thirteen windows having statistically significant coefficients.

Table 5.8. B. reports the results of the GGSECI, showing that for the entire sample period, there is an effect of investor overconfidence. The information criteria favour the EGARCH model with few windows for the TARCH. The effect of investor overconfidence did not appear in the period 2011-2013 but appeared in the period 2012-2014 until 2014-2016, then disappeared in the period 2015-2017 and 2016- 2018 to appear again in the period 2017-2019. These results suggest that investor overconfidence fluctuates over time, as the AMH suggests.

JALSH results are shown in Table 5.8. C., they confirm the presence of the investor overconfidence effect in the full sample. The rolling window estimates show that investors were overconfident during the initial window 2005-2007 and continued until 2007-2009. It then disappeared in the 2008-2010 and 2009-2011 windows, reappeared in the 2010-2012 window, and disappeared in the 2011-2013 window. It disappeared from the 2009-2011 window to the 2011-2013 window. It then reappeared from the 2012-2014 window going forward. The information criteria selected the EGARCH and the TARCH models. The effect of investor overconfidence disappears and reappears in the rolling windows in line with the AMH paradigm.

Table 5.8. D. presents the empirical results of the MOSENEW market index. The statistical significance of the parameter f_2 proves that there is an influence of investor overconfidence in the market. From the rolling window estimations, it is found that this effect appears in the first two windows, 2005-2007 and 2006-2008, then disappears in the next five windows and reappears in the 2012-2014 window until the window 2014-2016, then disappears again. Seven windows have the influence of the investor overconfidence.

Full NGXINDX sample results in Table 5.8. E. shows that investor overconfidence bias is present in the entire sample period, and from the rolling window, reports show that this effect varies in the cyclical version postulated by the AMH. The information criterion selected a mixture of the EGARCH and the TARCH models. The first period shows the impact of investor overconfidence until 2007-2009 and then disappears. The effect only reappears in the 2010-2012 window, then disappears in the 2011-2013 window until the 2013-2015 window. It then reappears again, showing traits of the AMH.

NSEASI results are presented in Table 5.8. F. shows the investor overconfidence effect in the full sample, although this effect appears and disappears within the rolling windows. The effect of investor overconfidence was present in the earlier windows, only to disappear in 2011-2013. It reappeared in the 2012-2014, 2013-2015, and 2014-2016 windows before disappearing again in the 2015-2017 window. It then reappears in the 2017-2019 window. The investor overconfidence effect moves in cyclical versions in support of the AMH.

The results of the full SEMDEX sample are depicted in Table 5.8. G and indicates the presence of an impact due to investor overconfidence in the market. However, the rolling window results show that the investor overconfidence effect fluctuates between significant and insignificant influence periods. The significant periods are 2005-2007, 2006-2008 and 2007-2009, then move on to the insignificant periods 2008-2010, 2009-2011 and 2011-2013, then back to the significant periods. The results show that the investor overconfidence effect is not an all-or-nothing phenomenon. The observed movement shows a cyclical motion according to the AMH paradigm.

From the results of all these markets, it was discovered that the impact of investor overconfidence changes over time. This empirical analysis supports the view that investor overconfidence is not static but appears and disappears over time. This result is consistent with the observations of Ataullah, Vivian, and Xu (2018), Lippi, Barbie, Piva, and De Bondt (2018), Bampinas, Panagiotidis, and Rouska (2019). Daniel and Hirshleifer (2015) posit that when people receive feedback on their judgments and decisions, their beliefs change over time. Their results show that investors' perceived precision varies over time based on the presence of public signals, which is consistent with the AMH supporting changes over time. Ataullah, Vivian, and Xu (2018) examined the impact of managerial overconfidence on the UK corporate debt maturity for UK firms and provided the first evidence of a positive relationship between overconfidence and debt maturity through overconfidence helping minimise the agency costs of long-term debt, consistent with the AMH hypothesis.

The results of this study contrast with the absolute approach observed for the full sample period, which was the basis for assessment within the EMH framework. The AMH appears to provide a more appropriate description of the behaviour of overconfident investors and the markets they trade-in. The cycles of market inefficiency (investor overconfidence) and the efficient markets appear and disappear in the selected African equity markets, as revealed by rolling window estimation results. Lo (2005) argues that the idea that developing markets must necessarily move towards some ideal equilibrium state is an illusion; hence, the African stock markets are a good example of adaptive markets. An important implication for investors and regulators is that different markets should be treated differently or not be viewed similarly, even if they have comparable characteristics.

Table 5.8. A. Rolling GARCH Results for Investor Overconfidence in the Egyptian Stock Market

EGX30						
SAMPLE	**MODEL**	$\boldsymbol{f_1}$	$\boldsymbol{f_2}$	$\boldsymbol{\eta}$	$\boldsymbol{k/\theta}$	$\boldsymbol{\delta}$
FULL	EGARCH (1, 1)	0.0127	0.1358	0.7469	-0.9964	0.7615
2005 - 2007	EGARCH (1, 1)	0.0172	0.1075	0.0299	0.0871	0.7961
2006 - 2008	EGARCH (1, 1)	0.1510	0.0763	0.0303	0.0881	0.7791
2007 - 2009	EGARCH (1, 1)	0.0307	0.1066	0.1096	-0.0702	0.8850
2008 - 2010	EGARCH (1, 1)	0.5080	0.0357	0.0246	0.0912	0.8255
2009 - 2011	EGARCH (1, 1)	0.4453	0.1227	0.1075	-0.0714	0.8916
2010 -2012	EGARCH (1,1)	0.1738	0.1291	0.1264	-0.0822	0.8861
2011 - 2013	EGARCH (1, 1)	0.0886	0.0617	0.1319	-0.0942	0.8967
2012 - 2014	TARCH (1, 1)	0.0769	0.1124	0.1233	0.0897	0.8983
2013 - 2015	TARCH (1, 1)	0.0438	0.0953	0.1194	0.1041	0.8955
2014 - 2016	TARCH (1, 1)	0.0112	0.0535	0.0616	-0.1073	0.9007
2015 - 2017	TARCH (1, 1)	0.0402	0.0370	0.0750	-0.1046	0.9047
2016 - 2018	GARCH (1, 1)	0.0336	0.0776	0.0718	-	0.9034
2017 - 2019	GARCH (1, 1)	0.0258	0.0654	0.0355	-	0.8593
REMARK	**ADAPTIVE**					

Source: Author (2023)

Table 5.8. B. Rolling GARCH Results for Investor Overconfidence in the Ghana Stock Exchange

GGSECI						
SAMPLE	**MODEL**	f_1	f_2	η	k/θ	δ
FULL	EGARCH (1, 1)	0.0229	0.1461	0.9553	0.1478	0.8193
2005 - 2007	n/a	n/a	n/a	n/a	n/a	n/a
2006 - 2008	n/a	n/a	n/a	n/a	n/a	n/a
2007 - 2009	n/a	n/a	n/a	n/a	n/a	n/a
2008 - 2010	n/a	n/a	n/a	n/a	n/a	n/a
2009 - 2011	n/a	n/a	n/a	n/a	n/a	n/a
2010 - 2012	n/a	n/a	n/a	n/a	n/a	n/a
2011 - 2013	TARCH (1, 1)	0.0841	0.0738	0.1419	0.1013	0.9648
2012 - 2014	EGARCH (1, 1)	0.0828	0.1209	0.1326	-0.0965	0.9662
2013 - 2015	EGARCH (1, 1)	0.0471	0.1026	0.1285	-0.1120	0.9636
2014 - 2016	EGARCH (1, 1)	0.0355	0.0966	0.0663	-0.1154	0.9693
2015 - 2017	EGARCH (1, 1)	0.0702	0.0614	0.0807	-0.1126	0.9735
2016 - 2018	EGARCH (1, 1)	0.0511	0.0203	0.0773	-0.1006	0.9719
2017 - 2019	TARCH (1, 1)	0.0277	0.0704	0.0381	0.1562	0.9245
REMARK	**ADAPTIVE**					

Source: Author (2023)

Table 5.8. C. Rolling GARCH Results for Investor Overconfidence in the Johannesburg Stock Exchange

JALSH						
SAMPLE	**MODEL**	f_1	f_2	η	k/θ	δ
FULL	EGARCH (1, 1)	0.0183	0.1954	0.5917	-0.8719	0.9550
2005 - 2007	TARCH (1, 1)	0.0202	0.1983	0.0430	0.1254	0.8555
2006 - 2008	TARCH (1, 1)	0.0810	0.2461	0.0436	0.1268	0.8372
2007 - 2009	EGARCH (1, 1)	0.0442	0.1533	0.1577	-0.1014	0.9510
2008 - 2010	EGARCH (1, 1)	0.1715	0.0192	0.0354	0.1312	0.8876
2009 - 2011	EGARCH (1, 1)	0.0652	0.0165	0.1548	-0.1027	0.9582
2010 - 2012	EGARCH (1, 1)	0.1031	0.1857	0.1814	-0.1183	0.9522
2011 - 2013	EGARCH (1, 1)	0.1274	0.1019	0.1898	-0.1355	0.9636
2012 - 2014	EGARCH (1, 1)	0.1108	0.1617	0.1773	-0.1291	0.9653
2013 - 2015	EGARCH (1, 1)	0.0631	0.1372	0.1718	-0.1498	0.9623
2014 - 2016	EGARCH (1, 1)	0.0302	0.0770	0.0886	-0.1544	0.9679
2015 - 2017	EGARCH (1, 1)	0.0206	0.0821	0.1079	-0.1506	0.9721
2016 - 2018	EGARCH (1, 1)	0.0484	0.1116	0.1033	-0.1346	0.9707
2017 - 2019	EGARCH (1, 1)	0.0371	0.0942	0.0518	0.2099	0.9234
REMARK	**ADAPTIVE**					

Source: Author (2023)

Table 5.8. D. Rolling GARCH Results for Investor Overconfidence in the Casablanca Stock Exchange

MOSENEW						
SAMPLE	**MODEL**	f_1	f_2	η	k/θ	δ
FULL	EGARCH (1, 1)	0.1690	0.1805	0.7602	-0.6530	0.9720
2005 - 2007	GARCH (1, 1)	0.0118	0.1347	0.0167	-	0.7780
2006 - 2008	GARCH (1, 1)	0.0250	0.1671	0.0296	-	0.7613
2007 - 2009	EGARCH (1, 1)	0.1041	0.0444	0.1071	-0.0684	0.0649
2008 - 2010	EGARCH (1, 1)	0.1326	0.0725	0.0240	0.0891	0.3067
2009 - 2011	TARCH (1, 1)	0.2130	0.1199	0.1058	-0.0697	0.1713
2010 - 2012	TARCH (1, 1)	0.3078	0.1261	0.1205	-0.0803	0.8659
2011 - 2013	TARCH (1, 1)	0.0896	0.0689	0.1289	-0.0920	0.7763
2012 - 2014	TARCH (1, 1)	0.0757	0.1098	0.1204	-0.0876	0.048
2013 - 2015	EGARCH (1, 1)	0.0428	0.0932	0.1167	-0.1017	0.5154
2014 - 2016	EGARCH (1, 1)	0.0523	0.0710	0.0602	-0.1048	0.0238
2015 - 2017	EGARCH (1, 1)	0.0557	0.0521	0.0733	-0.1023	0.4070
2016 - 2018	EGARCH (1, 1)	0.0328	0.0758	0.0702	-0.0914	0.2822
2017 - 2019	EGARCH (1, 1)	0.0252	0.0639	-0.0348	0.1422	0.8377
REMARK	**ADAPTIVE**					

Source: Author (2023)

Table 5.8. E. Rolling GARCH Results for Investor Overconfidence in the Nigerian Stock Exchange

NGXINDX						
SAMPLE	**MODEL**	f_1	f_2	η	k/θ	δ
FULL	EGARCH (1, 1)	0.0155	0.1656	0.3493	-0.4341	0.9285
2005 - 2007	EGARCH (1, 1)	0.0140	0.1681	0.0292	0.0851	0.0477
2006 - 2008	EGARCH (1, 1)	0.0551	0.2086	0.0296	0.0861	0.1296
2007 - 2009	EGARCH (1, 1)	0.0300	0.1299	0.1071	-0.0684	0.0424
2008 - 2010	EGARCH (1, 1)	0.1654	0.0628	0.0240	0.0892	0.6790
2009 - 2011	EGARCH (1, 1)	0.0496	0.0442	0.1050	-0.0696	0.1192
2010 - 2012	EGARCH (1, 1)	0.0721	0.1574	0.1236	-0.0804	0.0430
2011 - 2013	TARCH (1, 1)	0.1866	0.1118	0.1289	-0.0926	0.0549
2012 - 2014	TARCH (1, 1)	0.1752	0.1371	0.1204	-0.0878	0.0362
2013 - 2015	TARCH (1, 1)	0.1163	0.0428	0.1167	-0.1014	0.0534
2014 - 2016	TARCH (1, 1)	0.0652	0.0210	0.0602	-0.1024	0.1924
2015 - 2017	TARCH (1, 1)	0.0002	0.0696	0.0733	-0.1023	0.5604
2016 - 2018	TARCH (1, 1)	0.0328	0.0946	0.0702	-0.0911	0.1472
2017 - 2019	TARCH (1, 1)	0.0792	0.0708	0.0347	0.1492	0.6376
REMARK	**ADAPTIVE**					

Source: Author (2023)

Table 5.8. F. Rolling GARCH Results for Investor Overconfidence in the Nairobi Stock Exchange

NSEASI						
SAMPLE	**MODEL**	f_1	f_2	η	k/θ	δ
FULL	EGARCH (1, 1)	0.0099	0.1067	0.1536	0.5585	0.5941
2005 - 2007	n/a	n/a	n/a	n/a	n/a	n/a
2006 - 2008	n/a	n/a	n/a	n/a	n/a	n/a
2007 - 2009	n/a	n/a	n/a	n/a	n/a	n/a
2008 - 2010	EGARCH (1, 1)	0.1056	0.1266	0.01224	0.0712	0.4440
2009 - 2011	EGARCH (1, 1)	0.0352	0.0364	0.0848	-0.0576	0.0964
2010 - 2012	TARCH (1, 1)	0.0572	0.1192	0.0941	-0.0624	0.6904
2011 - 2013	TARCH (1, 1)	0.0664	0.0272	0.1030	-0.0735	0.1096
2012 - 2014	TARCH (1, 1)	0.0628	0.7896	0.0962	-0.0700	0.0132
2013 - 2015	TARCH (1, 1)	0.0372	0.0752	0.0935	-0.0813	0.6184
2014 - 2016	TARCH (1, 1)	0.0032	0.0414	0.0482	-0.0838	0.2424
2015 - 2017	TARCH (1, 1)	0.0612	0.0136	0.0576	-0.0817	0.0304
2016 - 2018	EGARCH (1, 1)	0.0728	0.0605	0.0516	-0.0730	0.3072
2017 - 2019	EGARCH (1, 1)	0.0296	0.0511	0.0268	0.1139	0.0976
REMARK	**ADAPTIVE**					

Source: Author (2023)

Table 5.8. G. Rolling GARCH Results for Investor Overconfidence in the Stock Exchange of Mauritius

SEMDEX						
SAMPLE	**MODEL**	f_1	f_2	η	k/θ	δ
FULL	EGARCH (1, 1)	0.2021	0.6630	0.4272	-0.9066	0.7375
2005 - 2007	EGARCH (1, 1)	0.1476	0.1481	0.0256	0.0746	0.6819
2006 - 2008	EGARCH (1, 1)	0.0482	0.1465	0.0260	0.0755	0.6673
2007 - 2009	EGARCH (1, 1)	0.0263	0.0913	0.0939	-0.0601	0.758
2008 - 2010	EGARCH (1, 1)	0.3068	0.1162	0.0210	0.07812	0.7071
2009 - 2011	EGARCH (1, 1)	0.0388	0.0149	0.0921	-0.0611	0.7637
2010 - 2012	EGARCH (1, 1)	0.0632	0.0612	0.1083	-0.0704	0.7590
2011 - 2013	EGARCH (1, 1)	0.0759	0.0735	0.1130	-0.0806	0.7681
2012 - 2014	TARCH (1, 1)	0.0659	0.0963	0.1056	-0.0768	0.7692
2013 - 2015	TARCH (1, 1)	0.0375	0.0817	0.1023	-0.0892	0.7671
2014 - 2016	TARCH (1, 1)	0.1843	0.4458	0.0528	-0.0919	0.7715
2015 - 2017	TARCH (1, 1)	0.0483	0.0295	0.0642	-0.0896	0.7749
2016 - 2018	GARCH (1, 1)	0.0288	0.0664	0.0615	-	0.7738
2017 - 2019	GARCH (1, 1)	0.0221	0.0560	0.0304	-	0.7361
REMARK	**ADAPTIVE**					

Source: Author (2023)

5.7 Summary

This section presents the empirical results, interpretation of the models estimated in the study, and in-depth discussion. This chapter begins by presenting the results of descriptive statistics and any other diagnostic tests relevant to the study. The objective was to provide information about the distributional characteristics of the return series in the selected markets. The next section presented the new measure of investor overconfidence. The third part presented the GMM dummy regression analysis results assuming the Markov switching model. The final section presented the results of the GARCH family models, specifically the EGARCH and the TARCH models. The study shows that investor overconfidence is present in all the selected African stock markets, but the extent varies between markets. The results show that the African markets exhibit similar behaviours to other markets. A discussion of the results of similar studies was also presented to verify the present study compared with results from the developed markets and some emerging Asian markets where the AMH has been administered. Regarding market conditions, the research showed that investor overconfidence in the African markets develops with changing conditions. From the rolling estimation results, the study submits that investor overconfidence is not static but rather adaptive and, thus, more consistent with the AMH than the EMH or the BF.

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

6.1 Summary

The efficient market hypothesis assumes that investors are rational and logical decision-makers, markets operate without friction, and stock prices accurately reflect all publicly available information. According to the EMH, shares are always traded on the stock market at their fair value, making it difficult for investors to buy shares to outperform the market. The BF school of thought arose from discovering market anomalies, which also led to the introduction of behavioural and psychological concepts into finance. According to the behavioural finance theory, investors are not always rational because their judgments are influenced by passions, emotions, and psychological and cognitive biases, such as investors' overconfidence, leading to unreasonable assessments of investment outcomes and detrimental to their investment activities. Most people believe that investor overconfidence is the cause of market inefficiency because it leads to mispricing in the form of excessive volatility and overestimating one's belief in the accuracy of their price forecasts. The analysis of investor overconfidence within the AMH framework in seven African stock markets, the Casablanca Stock Exchange, the Egyptian Exchange, the Johannesburg Stock Exchange, the Nigerian Stock Exchange, the Nairobi Securities Exchange, the Ghana Stock Exchange, and the Stock Exchange of Mauritius, was informed by this gap. The thesis comprises six chapters: the introduction, conceptualisation and theoretical framework, review of empirical literature, research methods and data, analysis and discussion of results, conclusions, and recommendations.

The first chapter presented the research context, problem set, research objectives and study motivation. It discussed the need to evaluate financial markets from a biological perspective. From the AMH perspective, market efficiency should not be static but dynamic. Likewise, the investor overconfidence should also be considered dynamic and context-dependent. The presence of the AMH in the African markets may indicate that investor overconfidence may be subject to market conditions and, therefore, needs to be investigated. The AMH framework provides an ideal opportunity to assess market efficiency and investor overconfidence in Africa's small and underdeveloped markets.

The second chapter provides an essential and comprehensive review of the relevant literature that provides the theoretical foundation and conceptual framework for investor overconfidence.

It provides an in-depth review of the major theories of stock return behaviour: the EMH, the BF and the AMH. BF suggests that even when all the necessary factors are in place to make sound decisions, investors may still not consistently make sound investment decisions. On the other hand, the AMH applies evolutionary ideas to economic behaviour, moving away from the rational reasoning of the EMH. According to the EMH, no learning or adaptation occurs because it assumes a static market environment. The market is continuously and efficiently balanced. Thus, there is no room for error for investors. The AMH framework recognises that markets are dynamic and that investors make mistakes and learn from them. They adapt their behaviours appropriately, so coming together towards equilibrium is unexpected to transpire at any juncture (Lo, 2005). The AMH claims that the BF and the EMH can indeed coexist in an intellectually satisfying way. This section also provided the theoretical framework for the study.

Chapter 3 extends the literature review by examining existing empirical research on investor overconfidence. It presented existing research findings on the topic and helped identify research gaps in the literature. This section first documented studies of investor overconfidence conducted in developed and emerging markets and in Africa. It also reviewed empirical studies conducted within the AMH framework, including time-varying investor overconfidence studies, investor overconfidence and stock return volatility studies and finally, investor overconfidence and market condition studies. The argument is whether market returns cause overconfident investors to trade more aggressively in subsequent periods and whether excessive trading by overconfident investors in the stock market contributes to excessive volatility observed or not. Several studies have been conducted, and there is still no conclusive conclusion on whether investor overconfidence is static or changes with time and market conditions. The empirical assessment also revealed that there is little empirical research on investor overconfidence within the AMH framework globally and mainly in emerging markets such as the African equity markets.

Chapter 4 comprehensively discussed the data sources, nature, and research methods used to achieve the research objectives. It explained how the research was conducted, providing a detailed account of the methods used to collect data, why they were chosen, and how the data were collected and analysed. Several tests and models were discussed, including preliminary and diagnostic tests, such as the ADF, KPSS, Jarque-Bera, and the ARCH effects test. The GMM dummy regression model evaluated how market conditions influence investor overconfidence levels. The MS-VAR model was also used to assess whether the return-volume relationship changes as market conditions change. The section also explored using a family of several GARCH models to model the impact of investor overconfidence on the volatility of stock returns. It explored the EGARCH and the TARCH models, which were also subjected to rolling window estimations to test whether the investor overconfidence changes over time, as the AMH predicts.

Chapter 5 presented the estimation results of the empirical methods and their discussion. A new investor overconfidence index was created, and the results showed that all seven markets showed the presence of the investor overconfidence bias. However, investor overconfidence was observed to vary between markets. Robustness checks were performed using a VAR model, and the results were consistent with the index. The GMM and the MSM regressions were used to examine the asymmetric response of trading volume to stock returns in bull and bear markets. The GMM results showed that investors are overconfident in all seven markets. The data analysis showed that in 2005-2007, investors were overconfident. In the 2008-2010 period, the level of overconfidence was low; in the 2011-2013 period, investors were not overconfident, and in 2014-2016 and 2017-2019, there was significant overconfidence. The Markov switching model results confirmed the GMM results. The results show that investors trade more strongly when the market is in a bullish phase than when in a bearish phase.

The study estimated the investor overconfidence using the GARCH, the EGARCH and the TARCH models. The results suggest that the high return volatility obtained in the African stock markets during the period may be partly explained from the investor overconfidence perspective. From the results, it was found that the seven selected markets show the effect of investor overconfidence. This empirical analysis supports the idea that investor overconfidence increases stock market volatility. The rolling estimates track changes in overconfident investor behaviour over time in the selected African equity markets. The results show that investor overconfidence changes over time. The rolling window results show that the investor overconfidence effect evolves cyclically over time. It appears in other windows, then disappears and reappears. This proves that the investors' overconfidence is not static but appears and disappears over time in support of the AMH.

6.2 Concluding remarks

Patterns of investor overconfidence that should not be observed if markets are efficient were observed in all the selected stock markets in Africa, raising doubts about their efficiency. The study provides empirical evidence of investor overconfidence before and under-confidence after the crisis. The study demonstrates that lagged stock market returns are positively and significantly related to the current market turnover due to the presence of investor overconfidence in the pre-crisis period of 2005-2007 and post-crisis 2014-2016 and 2017-2019. After suffering losses caused by the financial crisis, investors lose confidence, learn from their mistakes, and adapt their behaviours appropriately to changes in market conditions. Therefore, there was no indication of overconfident behaviour in the post-crash period 2011-2013.

The results highlight the impact of investor overconfidence on the volatility of stock returns in all the selected African stock markets and that this impact evolves according to time and market conditions. The empirical analysis supports the idea that investor overconfidence intensifies stock market volatility. The overconfident investor's trading exhibits a positive and significant relationship with volatility. Excessive investor confidence largely explains the excessive and asymmetric volatility in some African stock markets. The hypothesis that investor overconfidence changes over time and also due to changes in market conditions is valid for all the selected African stock markets, although at varying degrees. Therefore, the study concludes that investor overconfidence is time-variant and adaptive. Likewise, the selected African stock markets are good examples of adaptive markets, where cycles of inefficiency (investor overconfidence) and efficiency (no overconfidence behaviour) are repeated in the African stock markets.

6.3 Contributions and Implications of the Study

This doctoral thesis contributes to existing knowledge in several ways. Firstly, it provides a conventional measure of investor overconfidence in several selected African stock markets. A measure that combines multiple proxies into a single index and neutralizes the disadvantages of each proxy when used separately to check investor overconfidence. Secondly, it provides a timely contribution to the impact of investor overconfidence on stock return volatility in the African stock markets under the AMH model. Thirdly, it shows that investor overconfidence is not static and can, therefore, appear under specific market conditions and disappear under others, according to the AMH. Bias appears and disappears as market conditions change in the African stock markets. This also shows that investor overconfidence is normal, time-variant, and adaptable across the selected African stock markets. Fourthly, this study brings in a new perspective regarding investor overconfidence and market efficiency in the face of the AMH hypothesis.

These findings are vital for the investing public and stock brokers in creating appropriate investment strategies. This study provides important information to investors on whether different African stock markets display similar or different risk and return behaviour in the face of overconfident investors at the same time or should be viewed differently. This sheds more light on the appropriate investment strategies, trends, and models to adopt while taking advantage of any potential profit opportunities while preserving their wealth. The results show that different markets do not simultaneously exhibit the same return behaviour. Therefore, an implication of great importance for investors and stock brokers is that different markets should be treated differently or not be viewed similarly, even if they have comparable characteristics.

Furthermore, the study helps to clear up confusion regarding the effect of investor overconfidence on market efficiency, whether it creates inefficiencies, contributes to greater efficiency, or relates to an adaptive form of market efficiency. The results show that investor overconfidence contributes to an adaptive form of efficiency, as the selected African stock markets turn out to be adaptive, as the cycles of investor overconfidence (inefficiency) and the absence of overconfidence behaviour (efficiency) are repeated in the African stock market. This observation contradicts the studies of single-state models, in which most African markets have been considered inefficient over the years. Understanding investor overconfidence and its impact on individual decision-making, return volatility, and the stock market helps investment managers achieve better investment results and establish better client consulting relationships.

Observing time-varying investor overconfidence in the selected African markets implies that investor overconfidence can be detected in some periods other than at other stages. Therefore, when a test in absolute form shows no investor overconfidence, this implies that investor overconfidence is not always absent. Likewise, investor overconfidence is not always present when it is well documented in absolute form. This research helps investors understand the need to analyse their investments regularly, as excessive trading by overconfident investors can harm their returns. They should also have flexible investment plans to adapt to changes in market efficiency and investor overconfidence because markets are not always efficient or remain inefficient. Market regulators should also consider market dynamics when announcing rules and regulations related to the securities market. Policymakers should be cautious about the influence of investor overconfidence on price momentum during market booms.

6.4 Limitations of the study

Despite achieving the research goal, this thesis also reveals some general limitations common to this type of research. Firstly, the study focused on only seven African stock markets, shelving other markets that could provide greater insight into the nature of investor overconfidence and stock return volatility. However, the selected markets were still good enough in terms of diversity to reflect the investment behaviour of most African equity markets. Secondly, although there are some behavioural biases in the stock market, this study focused exclusively on investor overconfidence to explain the volatility of stock returns. However, investor overconfidence is considered the source of all other biases in the stock market because it creates the conditions for other biases to arise. Biases such as the disposition effect only explain the motivations of one side of a trade, while investor overconfidence can explain both sides of a given trade. Thirdly, this study used a shorter sample than similar studies conducted in the developed markets, where centuries of data are available. However, weekly data covering 2005 and 2019 has generated robust results and sufficient windows to track changes in investor overconfidence in the African stock markets. Fourthly, the study tested the adaptive nature of investor overconfidence in relation to performance and risk (returns and volatility) and did not consider other stock market quality measures such as liquidity and momentum. However, the chosen metrics were considered sufficient to track changes in investor overconfidence. Finally, the study only incorporated two market conditions: the bull and the bear market. AMH proponents acknowledge that external conditions such as the economic, political, social, cultural, and natural environments can provide additional insights into the behaviour of investors' overconfidence on the volatility of stock returns, as the market does not operate in a vacuum or isolation.

6.5 Recommendations for future studies

The link between investor overconfidence and the AMH is a relatively new phenomenon and thus allows research to venture in any direction. This study focused on only one type of bias, investor overconfidence, and assessed its effect on the volatility of stock returns. Further studies can be done by combining investor overconfidence with other biases, such as the disposition effect, confirmation bias and loss aversion. The combination of investor overconfidence and the disposition effect would be interesting, as these are two common mistakes that investors often make: (i) excessive trading due to investor overconfidence and (ii) the tendency to disproportionately retain losing investments while selling winners that is, those with the highest return, caused by the disposition effect (Barber & Odean, 1999). Overconfidence differs from the disposition effect in two ways. First, the disposition effect refers to an investor's attitude towards a specific security in a portfolio (Odean, 1998). However, overconfidence affects the stock market in general. Second, the disposition effect explains the motivation of only one side of the transaction. On the other hand, overconfidence can explain both sides of a given transaction. Therefore, future research is needed to examine the disposition effect and the investor overconfidence bias at the market level within the AMH context, as it has been claimed that the disposition effect can be another behavioural explanation for trading patterns observed in the market.

Lo (2017) identifies other market conditions to consider. These are external conditions such as the political, economic, social, cultural, and natural environment that can be integrated into future research to provide deeper insights into the behaviour of investor overconfidence on stock return volatility. Since stock market conditions cannot be separated from the general economic situation, the influence of economic conditions can significantly contribute. According to Pompian (2006), behavioural finance can be divided into micro and macro. Micro-behavioural finance analyses the behavioural biases that distinguish individual investors from the purely rational economic entities – homo economicus – from neoclassical economics. Macro-behavioural finance analyses market anomalies that distinguish financial markets from the efficient markets that traditional finance assumes. At the same time, it questions the informational efficiency of markets and asserts that behavioural influences influence financial markets. This current study was conducted at the macro level, but other studies suggest that the level of investor overconfidence varies according to individual portfolio returns. Therefore, future research is needed to examine the impact of investor overconfidence at the micro level, that is, at the individual investor level. There is also room for company or industry-specific measures.

The study focused on the adaptive behaviour of investor overconfidence in relation to performance and risk (returns and volatility) and did not consider other stock market quality measures such as liquidity and momentum. Therefore, future research is needed to look at the investor overconfidence and the other market quality factors such as liquidity and momentum.

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APPENDIX

Appendix 1: Survey on All African Stock Exchanges

	Economy	Stock Exchange	Short	Location	Currency	Founded
1	Algeria	Algiers Stock Exchange	SGBV	Algiers	DZD	1997
2	Angola	Angolan Stock Exchange *	BODIVA	Luanda	Kz	2014
3	Botswana	Botswana Stock Exchange *	BSE	Gaborone	BWP	1995
4	Cameroon	Douala Stock Exchange *	DSE	Douala	XAF	2001
5	Cape Verde	Bolsa de Valores de Cabo Verde (Cape Verde Stock Exchange) *	BCV	Praia	CVE	2005
6	CEMAC	Bourse des Valeurs Mobilières de l'Afrique Centrale *	BVMAC	Libreville (Gabon)	XAF	1994
7	Egypt	Egyptian Exchange *	EGX	Cairo/Alexandria	EGP	1883
8	Ghana	Ghana Stock Exchange *	GSE	Accra	GHS	1990
9	Kenya	Nairobi Stock Exchange *	NSE	Nairobi	KES	1954
10	Lesotho	Maseru Securities Exchange	MSM	Maseru	LSL	2016
11	Libya	Libyan Stock Market	LSM	Tripolis	LYD	2007
12	Malawi	Malawi Stock Exchange *	MSE	Blantyre	MWK	1996
13	Mauritius	Stock Exchange of Mauritius *	SEM	Port Louis	MUR	1988
14	Morocco	Casablanca Stock Exchange *	CSE	Casablanca	MAD	1929
15	Mozambique	Mozambique Stock Exchange *	BVM	Maputo	MZN	1999

16	Namibia	Namibian Stock Exchange *	NSX	Windhoek	NAD	1992
17	Nigeria	Nigerian Stock Exchange *	NGX	Lagos	NGN	1960
18		NASD OTC Securities Exchange *	NASD OTC	Lagos	NGN	1998
19		FMDQ Securities Exchange *	FMDQ	Lagos	NGN	2012
20	Rwanda	Rwanda Stock Exchange *	RSE	Kigali	RWF	2005
21	UEMOA	Bourse Régionale des Valeurs Mobilières *	BRVM	Abidjan (Côte d'Ivoire)	XOF	1998
22	Seychelles	Seychelles Securities Exchange / Merj Exchange *	Trop-X	Victoria	SCR	2012
23	Sierra Leone	Sierra Leone Stock Exchange	SLSE	Freetown	SLL	2009
24	Somalia	Somali Stock Exchange	SSE	Garowe	SOS	2015
25	South Africa	Johannesburg Stock Exchange *	JSE	Johannesburg	ZAR	1887
26		ZAR X	ZAR X	Johannesburg	ZAR	2016
27	Sudan	Khartoum Stock Exchange *	KSE	Khartoum	SDG	1994
28	Eswatini	Eswatini Stock Exchange *	SSX	Mbabane	SZL	1990
29	Tanzania	Dar Es Salaam Stock Exchange *	DSE	Dar Es Salaam	TZS	1998
30	Tunisia	Bourse des Valeurs Mobilières de Tunis *	BVMT	Tunis	TND	1969
31	Uganda	Uganda Securities Exchange *	USE	Kampala	UGX	1997
32		ALTX East Africa Exchange	ALTX	Kampala	UGX	2016
33	Zambia	Lusaka Stock Exchange *	LuSE	Lusaka	ZMK	1994
34	Zimbabwe	Zimbabwe Stock Exchange *	ZSE	Harare	ZWD	1946
35		Victoria Falls Stock Exchange	VFEX	Victoria Falls	USD	2020

Note: * represent exchanges who are members of ASEA

Source: Author compilation from websites of respective stock exchanges and ASEA

Appendix 11: Market Capitalisation of Selected African Markets

	Stock Exchange	MCAP in US $
1	Nigerian Stock Exchange (NGX)	68.9 bn
2	Ghana Stock Exchange (GSE)	7.5 bn
3	BRVM	9.6 bn
4	Uganda Securities Exchange (USE)	5.6 bn
5	Dar es Salaam Stock Exchange (DSE)	6.8 bn
6	Malawi Stock Exchange (MSE)	2.6 bn
7	Rwanda Stock Exchange (RSE)	3.7 bn
8	Nairobi Securities Exchange (NSE)	16.9 bn
9	Bourse des Valeurs Mobilières d'Afrique Centrale (BVMAC)	65.5 bn
10	Angolan Stock Exchange	93.9 m
11	Botswana Stock Exchange (BSE)	30.8 bn
12	Johannesburg Stock Exchange (JSE	1.2 trn
13	Namibian Stock Exchange (NSX)	2.4 bn
14	Stock Exchange of Mauritius (SEM)	7.8 bn
15	Tunis Stock Exchange (Bourse des Valeurs Mobilières de Tunis, BVMT)	7.2 bn
16	Bourse de Casablanca	62.9 bn
17	Egyptian Exchange (EGX)	34.9 bn

Source: Author compilation from ASEA (2022) report

Appendix 1II: Survey on All African Countries in African Union

	Member State	Abbreviation	Date of joining the OAU or AU
1	People's Democratic Republic of Algeria	Algeria *	25 May 1963
2	Republic of Angola	Angola *	11 February 1975
3	Republic of Benin	Benin *	25 May 1963
4	Republic of Botswana	Botswana *	31 October 1966
5	Burkina Faso	Burkina Faso *	25 May 1963
6	Republic of Burundi	Burundi	25 May 1963
7	Republic of Cabo Verde	Cabo Verde *	18 July 1975
8	Republic of Cameroon	Cameroon *	25 May 1963
9	Central African Republic	Central African Republic *	25 May 1963
10	Republic of Chad	Chad *	25 May 1963
11	Union of the Comoros	Comoros	18 July 1975
12	Republic of the Congo	Congo Republic *	25 May 1963
13	Republic of Côte d'Ivoire	Côte d'Ivoire *	25 May 1963
14	Democratic Republic of Congo	DR Congo	25 May 1963
15	Republic of Djibouti	Djibouti	27 June 1977
16	Arab Republic of Egypt	Egypt *	25 May 1963
17	Republic of Equatorial Guinea	Equatorial Guinea *	12 October 1968
18	State of Eritrea	Eritrea	24 May 1993
19	Kingdom of Eswatini	Eswatini *	24 September 1968
20	Federal Democratic Republic of Ethiopia	Ethiopia	25 May 1963
21	Gabonese Republic	Gabon *	25 May 1963
22	Republic of the Gambia	Gambia	9 March 1965
23	Republic of Ghana	Ghana *	25 May 1963
24	Republic of Guinea	Guinea	25 May 1963
25	Republic of Guinea-Bissau	Guinea-Bissau *	19 November 1973
26	Republic of Kenya	Kenya *	13 December 1963
27	Kingdom of Lesotho	Lesotho *	31 October 1966
28	Republic of Liberia	Liberia	25 May 1963
29	Libya	Libya *	25 May 1963
30	Republic of Madagascar	Madagascar	25 May 1963

31	Republic of Malawi	Malawi *	13 July 1964
32	Republic of Mali	Mali *	25 May 1963
33	Islamic Republic of Mauritania	Mauritania	25 May 1963
34	Republic of Mauritius	Mauritius *	August 1968
35	Kingdom of Morocco	Morocco *	1963 / 31 January 2017
36	Republic of Mozambique	Mozambique *	18 July 1975
37	Republic of Namibia	Namibia *	June 1990
38	Republic of Niger	Niger *	25 May 1963
39	Federal Republic of Nigeria	Nigeria *	25 May 1963
40	Republic of Rwanda	Rwanda *	25 May 1963
41	Sahrawi Arab Democratic Republic	Sahrawi Republic	22 February 1982
42	Democratic Republic of São Tomé and Príncipe	São Tomé and Príncipe	18 July 1975
43	Republic of Senegal	Senegal *	25 May 1963
44	Republic of Seychelles	Seychelles *	29 June 1976
45	Republic of Sierra Leone	Sierra Leone *	25 May 1963
46	Federal Republic of Somalia	Somalia *	25 May 1963
47	Republic of South Africa	South Africa *	6 June 1994
48	Republic of South Sudan	South Sudan	27 July 2011
49	Republic of the Sudan	Sudan *	25 May 1963
50	Togolese Republic	Togo *	25 May 1963
51	Republic of Tunisia	Tunisia *	25 May 1963
52	Republic of Uganda	Uganda *	25 May 1963
53	United Republic of Tanzania	Tanzania *	25 May 1963
54	Republic of Zambia	Zambia *	16 December 1964
55	Republic of Zimbabwe	Zimbabwe *	18 June 1980

Note: * represent countries with or represented by a stock exchange

Source: Author compilation from African Union (2022) and ASEA (2022) reports

Appendix 1V: Lag structure criteria for the endogenous variables in the market wide VAR model

Lag	Log Lik	LR	FPE	AIC	SBIC	HQIC
0	452.61096	N/A	0.000258	-3.65790216	-3.0940632	-3.2602356
1	463.06008	20.346348	0.0002484	-3.70480044	-3.14106	-3.2315004
2	473.559	6.3923208	0.0002472	-3.71226372	-3.0181632	-3.2768196 *
3	470.22444	13.842072 *	0.0002448 *	-3.72443016 *	-3.1632648 *	-3.2686116
4	474.63876	2.0533848	0.0002532	-3.68137836	-2.9252448	-3.1773696
5	475.11924	0.906768	0.0002604	-3.64551924	-2.8278048	-3.1187184
6	476.87424	3.2846916	0.0002652	-3.6202386	-2.7399828	-3.0696852
7	478.04892	2.1809724	0.0002712	-3.5901426	-2.647782	-3.0162732
8	479.91732	3.4406508	0.000276	-3.56580444	-2.5608156	-2.9680956

Appendix V: Rolling GARCH Information Criteria

		EGX	**GGSECI**	**JALSH**	**MOSENEW**	**NGXINDX**	**NSEASI**	**SEMDEX**
Model	**IC**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**
GARCH (1, 1)	AIC	3.5604816	2.7440688	2.7751116	2.1082848	3.5746416	2.7579972	1.2367056
	SBIC	3.5744688	2.7569304	3.9032484	0.8374944	3.9134244	3.9042528	0.8299932
	HQIC	2.7546	3.5553024	1.2486636	2.1205512	1.4542608	1.8439548	3.9456876
	Log Lik	-8958.0516	-2421.6756	-500.5392	-493.45944	-2425.902	-2419.62	-1064.75688
EGARCH (1, 1)	AIC	**2.55167848**	**1.96658264**	**1.98882998**	**1.51093744**	**2.56182648**	**1.97656466**	**0.88630568**
	SBIC	**2.56170264**	**1.97580012**	**2.79732802**	**0.60020432**	**2.80462082**	**2.79804784**	**0.59482846**
	HQIC	**1.97413**	**2.54796672**	**0.89487558**	**1.51972836**	**1.04222024**	**1.32150094**	**2.82774278**
	Log Lik	**-6419.93698**	**-1735.53418**	**-358.71976**	**-353.645932**	**-1738.5631**	**-1734.061**	**-763.075764**
TARCH (1, 1)	AIC	2.72970256	2.10378608	2.12758556	1.61635168	2.74055856	2.11446452	0.94814096
	SBIC	2.74042608	2.11364664	2.99249044	0.64207904	3.00029204	2.99326048	0.63632812
	HQIC	2.11186	2.72573184	0.95730876	1.62575592	1.11493328	1.41369868	3.02502716
	Log Lik	-6867.83956	-1856.61796	-383.74672	-378.318904	-1859.8582	-1855.042	-816.313608
2005-2007								
GARCH (1, 1)	AIC	2.5220078		1.96570405	**1.42309224**	2.5320378		0.8759998

		EGX	GGSECI	JALSH	MOSENEW	NGXINDX	NSEASI	SEMDEX
Model	**IC**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**
	SBIC	2.5319154		2.76480095	**0.56530872**	2.77200895		0.58791185
	HQIC	1.951175		0.88447005	**1.43137206**	1.0301014		2.79486205
	Log Lik	-6345.28655		-354.5486	**-333.085122**	-1718.34725		-754.20279
EGARCH (1, 1)	AIC	**2.40332508**		2.03970702	1.567158368	**2.41288308**		**0.83477628**
	SBIC	**2.41276644**		2.86888757	0.622537504	**2.64156147**		**0.56024541**
	HQIC	**1.859355**		0.91776774	1.576276392	**0.98162604**		**2.66333913**
	Log Lik	**-6046.68483**		-367.896312	-366.8048504	**-1637.48385**		**-718.710894**
TARCH (1, 1)	AIC	2.64662466		**1.87320033**	1.4933684	2.657150256		0.919284496
	SBIC	2.65702181		**2.63469267**	0.5932252	2.908978804		0.616961612
	HQIC	1.96112054		**0.8368773**	0.74864004	2.669862356		0.6864546
	Log Lik	-6114.63581		**-340.556967**	-344.2548772	1654.998324		-700.328847
2006-2008								
GARCH (1, 1)	AIC	2.90772664		2.17383742	**1.5812136**	2.91929064		0.96875272
	SBIC	2.91914952		3.05754458	**0.6281208**	3.19596326		0.65016134
	HQIC	2.24959		0.97811982	**1.5904134**	1.18764632		3.09078862
	Log Lik	-7315.74214		-392.08904	**-370.09458**	-1981.1533		-834.059556
EGARCH (1, 1)	AIC	**2.6703612**		2.26634114	1.65148976	**2.6809812**		**0.9275292**
	SBIC	**2.6808516**		3.18765286	0.65603728	**2.9350683**		**0.6224949**
	HQIC	**2.06595**		1.01974194	1.66109844	**1.0906956**		**2.9592657**
	Log Lik	**-6718.5387**		-408.77368	-386.543228	**-1819.4265**		**-798.56766**
TARCH (1, 1)	AIC	2.78904392		**2.0813337**	1.72176592	2.80013592		1.00997624
	SBIC	2.80000056		**2.9274363**	0.68395376	3.06551578		0.67782778
	HQIC	2.15777		**0.9364977**	1.73178348	1.13917096		3.22231154
	Log Lik	-7017.14042		**-375.4044**	-402.991876	-1900.2899		-869.551452
2007-2009								
GARCH (1, 1)	AIC	2.62585518		2.13914852	1.55486004	2.7554529		0.91207038
	SBIC	2.63617074		3.00875397	0.61765212	3.016597975		0.612119985
	HQIC	2.0315175		0.96251152	1.56390651	1.1209927		2.909944605
	Log Lik	-6606.56306		-385.8323	-363.926337	-1869.966125		-785.258199
EGARCH (1, 1)	AIC	**2.5089527**		**1.95552864**	**1.485638022**	**2.518930781**		**0.871465213**

		EGX	GGSECI	JALSH	MOSENEW	NGXINDX	NSEASI	SEMDEX
Model	**IC**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**
	SBIC	**2.51880901**		**2.75048903**	**0.590154387**	**2.757659727**		**0.584868542**
	HQIC	**1.9410748**		**0.87989161**	**1.494281746**	**1.02476911**		**2.780394529**
	Log Lik	**-6905.16478**		**-390.00346**	**-384.487147**	**-1890.181975**		**-829.623069**
TARCH (1, 1)	AIC	2.7445379		2.04664480	1.6251362	2.63629818		0.9532939
	SBIC	2.7553197		2.87864569	0.6455686	2.886150495		0.639786425
	HQIC	2.1233375		0.92088940	1.63459155	1.07251734		3.041467525
	Log Lik	-6905.16478		-369.14766	-380.374985	-1789.102725		-820.750095
2008-2010								
GARCH (1, 1)	AIC	3.25157422		2.53434291	1.925370011	3.264505695	2.51871336	1.129409022
	SBIC	3.26434789		3.56460256	0.764833386	3.573895699	3.56551982	0.75798299
	HQIC	2.5156109		1.14032954	1.936572178	1.328089133	1.68397328	3.603359744
	Log Lik	-8180.85104		-457.112419	-450.646899	-2215.430742	-2209.6937	-972.378573
EGARCH (1, 1)	AIC	**2.1015624**		**1.63800037**	**1.244408076**	**2.109920289**	**1.62789865**	**0.729961358**
	SBIC	**2.10981829**		**2.30387935**	**0.494328278**	**2.309885707**	**2.30447220**	**0.48990072**
	HQIC	**1.62589347**		**0.73701952**	**1.251648277**	**0.85837259**	**1.08838817**	**2.328928954**
	Log Lik	**-5287.4601**		**-295.441594**	**-291.2627896**	**-1431.880569**	**-1428.1726**	**-628.469199**
TARCH (1, 1)	AIC	2.35824464		1.83806371	1.396398543	2.367623351	1.82672818	0.819117938
	SBIC	2.3675089		2.58527234	0.554704924	2.592012299	2.58593759	0.549736589
	HQIC	1.82447809		0.82703818	1.404523054	0.963213159	1.22132256	2.613381464
	Log Lik	-5933.26395		-331.526466	-326.8372675	-1606.768696	-1602.6078	-705.229652
2009-2011								
GARCH (1, 1)	AIC	3.11510096		2.42797289	1.844559454	3.127489682	2.41299933	1.082006096
	SBIC	3.1273385		3.41499105	0.732732226	3.423894142	3.41586981	0.726169351
	HQIC	2.41002709		1.09246827	1.85529145	1.272347317	1.61329449	3.452121538
	Log Lik	-7837.48893		-437.926751	-431.7325987	-2122.445919	-2116.9497	-931.566442
EGARCH (1, 1)	AIC	**2.12970741**		**1.65993716**	1.397405601	**2.138177235**	**1.64970016**	**0.73973731**
	SBIC	**2.13807387**		**2.33473388**	0.494328278	**2.340820675**	**2.33533466**	**0.496461678**
	HQIC	**1.64766812**		**0.74689000**	1.251648277	**0.869868279**	**1.10296433**	**2.360118956**
	Log Lik	**-5358.272**		**-299.398273**	-291.2627896	**-1451.05692**	**-1447.2993**	**-636.885925**
TARCH (1, 1)	AIC	2.52459271		1.96771878	**1.349055603**	2.53463299	1.95558365	0.876897648

		EGX	GGSECI	JALSH	MOSENEW	NGXINDX	NSEASI	SEMDEX
Model	**IC**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**
	SBIC	2.53451046		2.76763470	**0.535898429**	2.774850096	2.76834688	0.588514425
	HQIC	1.95317484		0.88537658	**1.356904664**	1.031157193	1.30747336	2.797726619
	Log Lik	-6351.7901		-354.911991	**-315.7563068**	-1720.108455	-1715.6544	-754.975803
2010-2012								
GARCH (1, 1)	AIC	3.42473792		2.66931022	2.027906252	3.438358067	2.65284830	1.189556088
	SBIC	3.43819186		3.75443670	0.805564851	3.764224743	3.75540281	0.798349635
	HQIC	2.64958063		1.20105818	2.039704995	1.398816976	1.77365385	3.795257905
	Log Lik	-8616.52508		-481.456098	-474.6462544	-2333.414268	-2327.3717	-1024.16293
EGARCH (1, 1)	AIC	**2.35222985**		**1.83337567**	1.801771744	**2.361584644**	2.35702568	**0.817028749**
	SBIC	**2.36147048**		**2.57867851**	0.715735249	**2.58540128**	3.33663287	**0.548334467**
	HQIC	**1.81982469**		**0.82492874**	1.812254793	**0.96075645**	1.57587137	**2.606715942**
	Log Lik	**-5918.13095**		**-330.680896**	-421.7178229	**-1602.670575**	-2067.8434	**-703.430939**
TARCH (1, 1)	AIC	3.25513209		2.53711599	**1.490011652**	3.268077715	**1.94919015**	1.130644821
	SBIC	3.26791973		3.56850295	**0.591891767**	3.577806254	**2.75929616**	0.758812375
	HQIC	2.51836348		1.14157729	**1.498680822**	1.329542327	**1.30319876**	3.607302538
	Log Lik	-8189.80253		-457.612591	**-348.7480987**	-2217.854865	**-1710.0450**	-973.442549
2011-2013								
GARCH (1, 1)	AIC	3.48079357	2.68265310	2.71300113	2.061098749	3.494636649	2.69626977	1.209026582
	SBIC	3.49446772	2.69522684	3.81588881	0.818750228	3.825837067	3.81687073	0.811416914
	HQIC	2.69294861	3.47573028	1.22071694	2.073090612	1.421712624	1.80268478	3.857378176
	Log Lik	-8757.5592	-2367.47547	-489.336506	-482.4152005	-2371.607279	-2365.4658	-1040.92629
EGARCH (1, 1)	AIC	**2.34035773**	1.88644164	**1.82412230**	1.449364624	2.457428464	1.89601688	**0.812905061**
	SBIC	**2.34955173**	1.89528349	**2.56566346**	0.575745154	2.690328595	2.68402347	**0.545566926**
	HQIC	**1.81063972**	2.44413350	**0.82076523**	1.457797302	0.999748306	1.26764792	**2.593559388**
	Log Lik	**-5888.2611**	-1664.80873	**-329.011891**	-339.2343652	-1667.71422	-1663.3959	**-699.880599**
TARCH (1, 1)	AIC	2.61846336	**1.92955815**	2.04088347	**1.482491301**	**2.513595448**	**1.93935224**	0.909502888
	SBIC	2.62874988	**1.93860209**	2.87054226	**0.588904385**	**2.751818744**	**2.74536951**	0.610396858
	HQIC	2.02579875	**2.49999662**	0.91829708	**1.491116716**	**1.022598553**	**1.29662128**	2.901753068
	Log Lik	-6587.96548	**-1702.8596**	-368.108503	**-346.9879057**	**-1705.831495**	**-1701.4141**	-783.047686
2012-2014								

		EGX	GGSECI	JALSH	MOSENEW	NGXINDX	NSEASI	SEMDEX
Model	**IC**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**
GARCH (1, 1)	AIC	2.83406367	2.18421734	2.20892672	1.678147515	2.845334709	2.19530404	0.984389979
	SBIC	2.84519716	2.19445489	3.10689836	0.666626798	3.114998235	3.10769784	0.660656011
	HQIC	2.19259995	2.82994113	0.99390827	1.687911295	1.157559049	1.46774675	3.14067902
	Log Lik	-7130.40858	-1927.59957	-398.418000	-392.78267	-1930.963697	-1925.9637	-847.522646
EGARCH (1, 1)	AIC	2.13299189	**1.46699050**	**1.48358611**	1.263018569	2.141474776	1.65224436	0.740878148
	SBIC	2.14137126	**1.47386637**	**2.08669270**	0.501721105	2.344430737	2.33893627	0.497227331
	HQIC	1.65020919	**1.90067934**	**0.66754071**	1.270367051	0.871209808	1.10466534	2.363758781
	Log Lik	-5366.53564	**-1294.63777**	**-267.590322**	-295.6187115	-1453.29477	-1449.5319	-637.868144
TARCH (1, 1)	AIC	**2.03624687**	1.75859093	1.77848532	**1.205732485**	**2.044345004**	**1.57730436**	**0.707274518**
	SBIC	**2.04424618**	1.76683354	2.50147418	**0.478964798**	**2.238095596**	**2.23285033**	**0.474674846**
	HQIC	**1.5753615**	2.27848608	0.80023084	**1.212747664**	**0.831694792**	**1.05456160**	**2.256546987**
	Log Lik							
				2013-2015				
GARCH (1, 1)	AIC	2.77347195	2.13751921	2.16170031	1.642269056	2.784502021	2.14836888	0.963343917
	SBIC	2.78436742	2.14753788	3.0404735	0.65237445	3.048400195	3.04125588	0.646531317
	HQIC	2.1457226	2.76943756	0.97265871	1.651824088	1.132810667	1.43636661	3.07353193
	Log Lik	-6977.96187	-1886.38883	-389.899903	-384.3850549	-1889.680079	-1884.7865	-829.402781
EGARCH (1, 1)	AIC	2.08818949	**1.43257598**	**1.44878227**	**1.100656872**	2.096494197	1.61753981	0.725316382
	SBIC	2.09639285	**1.43929055**	**2.03774042**	**0.437224594**	2.295187172	2.28980811	0.486783326
	HQIC	1.61554739	**1.85609079**	**0.6518807**	**1.107060702**	0.852910492	1.08146241	2.31410924
	Log Lik	-5253.81431	**-1264.26652**	**-261.312850**	**-257.6167715**	-1422.769059	-1419.0842	-624.47005
TARCH (1, 1)	AIC	**1.98847801**	1.72165263	1.74112915	1.322756222	**1.996386172**	**1.54031963**	**0.690682377**
	SBIC	**1.99628967**	1.72972211	2.44893199	0.525451271	**2.185591517**	**2.18046930**	**0.463539323**
	HQIC	**1.53840467**	2.23062765	0.78342240	1.330452268	**0.812183843**	**1.02982236**	**2.203610052**
	Log Lik	**-5002.94361**	-1519.38033	-314.042648	-309.600745	**-1354.831546**	**-1351.3214**	**-594.651478**
				2014-2016				
GARCH (1, 1)	AIC	4.2647057	3.28681542	3.32399814	2.525280342	4.281666387	3.30349870	1.481312364
	SBIC	4.28145941	3.30222090	4.67526799	1.00314158	4.687456699	4.67647105	0.994156725
	HQIC	3.29942958	4.25850210	1.49563552	2.539972901	1.741897589	2.20866877	4.726101205
	Log Lik	-10729.8557	-2900.65639	-599.540347	-591.0602892	-2905.718731	-2898.1942	-1275.35408

		EGX	GGSECI	JALSH	MOSENEW	NGXINDX	NSEASI	SEMDEX
Model	**IC**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**
EGARCH (1, 1)	AIC	2.95531064	**2.19722345**	**2.22207996**	**1.688140183**	2.967063878	2.28922358	1.026504171
	SBIC	2.96692045	**2.20752195**	**3.12539865**	**0.670596283**	3.248264155	3.24065144	0.68892021
	HQIC	2.28640381	**2.84679225**	**0.99982658**	**1.697962102**	1.207081764	1.53053992	3.275043616
	Log Lik	-7435.46187	**-1939.07762**	**-400.790413**	**-395.1215269**	-2013.574227	-2008.3597	-883.781378
TARCH (1, 1)	AIC	**3.04984208**	2.43656927	2.46413342	1.872031038	**3.061971268**	**2.36244891**	**1.059338932**
	SBIC	**3.06182325**	2.44798960	3.46585155	0.743645029	**3.35216629**	**3.34431006**	**0.710956682**
	HQIC	**2.35953894**	3.15689628	1.10873872	1.882922869	**1.245692655**	**1.57949726**	**3.379802345**
	Log Lik	**-7673.29978**	-2150.30335	-444.448927	-438.1625232	**-2077.98237**	**-2072.6013**	**-912.050868**
2015-2017								
GARCH (1, 1)	AIC	4.27962016	3.29831006	3.33562278	2.534111715	4.296640168	3.31505165	1.486492788
	SBIC	4.29643247	3.31376938	4.69161827	1.006649752	4.703849603	4.69282554	0.997633475
	HQIC	3.3109683	4.27339487	1.50086603	2.548855657	1.747989328	2.2163929	4.742629256
	Log Lik	-10767.38	-2910.80052	-601.637051	-593.1273365	-2915.880567	-2908.3974	-1279.81423
EGARCH (1, 1)	AIC	2.98950014	**2.22454479**	**2.24971037**	**1.709131335**	3.001389356	2.31570724	1.038379631
	SBIC	3.00124427	**2.23497135**	**3.16426136**	**0.678934801**	3.285842793	3.27814200	0.696890216
	HQIC	2.31285484	**2.88219064**	**1.01225891**	**1.719075384**	1.221046296	1.54824649	3.312932061
	Log Lik	-7521.48152	**-1963.18905**	**-405.774035**	**-400.0346591**	-2036.868938	-2031.5943	-894.0057
TARCH (1, 1)	AIC	**3.08776529**	2.46475754	2.49264058	1.893688259	**3.1000453**	**2.39182475**	**1.072511265**
	SBIC	**3.09989544**	2.47630999	3.50594742	0.752248137	**3.393848748**	**3.38589483**	**0.719797061**
	HQIC	**2.38887859**	3.19341789	1.12156554	1.904706096	**1.2611822**	**1.59913749**	**3.421828443**
	Log Lik	**-7768.71331**	-2175.17986	-449.590684	-443.2315539	**-2103.821008**	**-2098.3735**	**-923.39175**
2016-2018								
GARCH (1, 1)	AIC	**3.28561692**	3.20819423	3.24448754	2.464875204	4.179248194	3.22447845	**1.236708862**
	SBIC	**3.22636071**	3.22323121	4.56343478	0.979146261	4.575331931	4.56460906	**0.788493562**
	HQIC	**3.10271748**	4.15663800	1.45985966	2.479216314	1.7002311	2.15583704	**3.748403324**
	Log Lik	**-10090.1413**	-2831.27219	-585.19924	-576.9220258	-2836.213441	-2828.8692	**-1064.75969**
EGARCH (1, 1)	AIC	3.39161228	**2.21511301**	**2.24017190**	**1.701884847**	3.250229779	**2.22635653**	1.503984311
	SBIC	3.40493609	**2.22549537**	**3.15084532**	**0.676056209**	3.329528557	**3.15165611**	1.009372603
	HQIC	2.62395267	**2.86997054**	**1.00796707**	**1.711786735**	1.237280286	**1.48850797**	4.798435656
	Log Lik	-8533.1821	**-1954.86539**	**-404.053607**	**-398.3385658**	-2063.949411	**-1953.2064**	-1294.87377

		EGX	GGSECI	JALSH	MOSENEW	NGXINDX	NSEASI	SEMDEX
Model	**IC**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**	**OVER**
TARCH (1, 1)	AIC	3.32673169	2.49752686	2.52578060	1.918865124	**3.086901523**	2.51020385	1.326179759
	SBIC	3.25331925	2.50923290	3.55255951	0.762249386	**3.304112916**	3.55347367	0.819054947
	HQIC	2.50711188	3.23587485	1.13647692	1.930029444	**1.255834957**	1.67828395	3.591185747
	Log Lik	-8153.21193	-2204.09920	-455.568058	-449.1243827	**-2094.901089**	-2202.2289	-969.09338
2017-2019								
GARCH (1, 1)	AIC	**2.27044039**	2.40840851	2.43565409	1.850394955	3.137383897	2.42063316	**0.788619818**
	SBIC	**2.19389381**	2.25452887	3.42579482	0.735050318	3.43472607	3.42667636	**0.529268312**
	HQIC	**1.75654752**	3.12041030	1.09592443	1.861160903	1.27637255	1.61839835	**2.516077743**
	Log Lik	**-5712.35144**	-2125.45113	-439.312188	-433.0984401	-2129.160549	-2123.6468	**-678.971921**
EGARCH (1, 1)	AIC	2.33164261	1.84402106	**1.66599890**	**1.265678887**	3.001389356	**1.65572451**	0.831072732
	SBIC	2.40484493	1.85266408	**2.34325983**	**0.502777888**	3.285842793	**2.34386281**	0.557759839
	HQIC	1.85110583	2.38917205	**0.74961748**	**1.273042846**	1.221046296	**1.10699211**	2.651523025
	Log Lik	-6019.85826	-1627.37202	**-300.491611**	**-296.2413781**	-2036.868938	**-1452.5845**	-715.522279
TARCH (1, 1)	AIC	2.39579958	**1.76230337**	1.99499832	1.515623601	**2.295705312**	1.98269496	0.88905455
	SBIC	2.46026626	**1.77056338**	2.80600391	0.602065849	**2.513278305**	2.80672596	0.596673316
	HQIC	1.85353283	**2.28329603**	0.89765103	1.524441786	**0.933954957**	1.32559956	2.836513003
	Log Lik	-6027.75093	**-1555.25513**	-359.832326	-354.7427622	**-1557.962093**	-1739.4398	-765.442438

The selected models are put in bold. The model selection was based on the minimum AIC, SBIC & HQIC.

Appendix VI: Ethical Clearance Letter

UNIVERSITY OF KWAZULU-NATAL
INYUVESI YAKWAZULU-NATALI

Mr Jameson Nyasha (218028168)
School Of Acc Economics&Fin
Westville

Dear Mr Jameson Nyasha,

Protocol reference number: 00010754
Project title: Analysis of investor overconfidence under the adaptive markets hypothesis in selected African stock markets

Exemption from Ethics Review

In response to your application received on 14 April 2021 , your school has indicated that the protocol has been granted **EXEMPTION FROM ETHICS REVIEW.**

Any alteration/s to the exempted research protocol, e.g., Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through an amendment/modification prior to its implementation. The original exemption number must be cited.

For any changes that could result in potential risk, an ethics application including the proposed amendments must be submitted to the relevant UKZN Research Ethics Committee. The original exemption number must be cited.

In case you have further queries, please quote the above reference number.

PLEASE NOTE:
Research data should be securely stored in the discipline/department for a period of 5 years.

I take this opportunity of wishing you everything of the best with your study.

Yours sincerely,

[redacted] 16 April 2021

Prof Josue Mbonigaba
Academic Leader Research
School Of Acc Economics&Fin

UKZN Research Ethics Office
Westville Campus, Govan Mbeki Building
Postal Address: Private Bag X54001, Durban 4000
Website: http://research.ukzn.ac.za/Research-Ethics/

Founding Campuses: Edgewood Howard College Medical School Pietermaritzburg Westville

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Appendix VII: Amended Ethical Clearance Letter for Change in Tittle

UNIVERSITY OF
KWAZULU-NATAL
INYUVESI
YAKWAZULU-NATALI

9 October 2023

Mr Jameson Nyasha (218028168)
School Of Acc Economics&Fin
Westville

Dear Mr Jameson Nyasha,

Original application number: 00010754
Project title: Analysis of investor overconfidence under the adaptive markets hypothesis in selected African stock markets
Amended title: Investor overconfidence under the adaptive markets hypothesis in selected African stock markets

Exemption from Ethics Review

In response to your **amendment** application received on 6 oct 2023 , your school has indicated that the amendment has been granted **EXEMPTION FROM ETHICS REVIEW.**

Any alteration/s to the exempted research protocol, e.g., Title of the Project, Location of the Study, Research Approach and Methods must be reviewed and approved through an amendment/modification prior to its implementation. The original exemption number must be cited.

For any changes that could result in potential risk, an ethics application including the proposed amendments must be submitted to the relevant UKZN Research Ethics Committee. The original exemption number must be cited.

In case you have further queries, please quote the above reference number.

PLEASE NOTE:
Research data should be securely stored in the discipline/department for a period of 5 years.

I take this opportunity of wishing you everything of the best with your study.

Yours sincerely,

[redacted]

Prof Josue Mbonigaba
Academic Leader Research
School Of Acc Economics&Fin

UKZN Research Ethics Office
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Appendix VIII: Language Editing Certificate

C Woudberg

Language Practitioner

cwoudberg@gmail.com | +27 74 338 7289

To whom this may concern:

I hereby confirm that I have completed the language and technical editing of the research paper titled **Investor overconfidence under the adaptive markets hypothesis in selected African stock markets** by Jameson Nyasha. My involvement was restricted to language usage, spelling, completeness and consistency, referencing style and general technical formatting. I did no structural re-writing of the content and did not influence the academic content in any way.

[redacted]

Kind regards,

Christelle Woudberg

ND Language Practice

Member of the South African Translators 'Institute