MARKET TIMING AND PORTFOLIO RETURNS: AN EMPIRICAL ANALYSIS OF THE POTENTIAL PROFITABILITY OF BUY-SELL STRATEGIES, BASED ON SOUTH AFRICAN EQUITIES, 2009-2018

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Thesis submitted in partial fulfilment of the requirement for the degree of

MASTER OF COMMERCE IN FINANCIAL MARKETS

(Half thesis)

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ACKNOWLEDGMENTS

I would like to take this opportunity to thank my supervisors, Prof Hugo Nel and Dr. Sibanisezwe Khumalo for their ongoing support, immense knowledge and motivation from day one till the submission date. I would also like to thank my family for supporting me spiritually throughout writing this thesis and my life in general.

ABSTRACT

South Africa's financial markets have become larger and more complex over recent decades. The number of market participants who are using technical analysis techniques to predict the market's movement has been growing rapidly. This research aims to investigate if historical share prices can be used when forecasting the market's direction and to examine the profitability of the Japanese candlestick patterns. The study is based on ten companies selected from the JSE top 40 2019 composition. These are Aspen Pharmacy Holding, Capitec Bank Holding LTD, Discovery LTD, Kumba Iron Ore LTD, Mondi PLC, Mr. Price Group LTD, MTN Group LTD, Naspers LTD, SASOL LTD, and Shoprite Holdings LTD. These were selected from the JSE top 40 based on market capitalization and sector.

This research analyzes eight candlestick reversal patterns; four are bullish patterns namely: doji star, hammer, bullish engulfing and the piercing lines and the other four are bearish patterns namely: shooting star, hanging man, bearish engulfing and the dark cloud cover. The ARCH and GARCH models are used to test for correlation between past share prices and future share prices and the binomial test and the mean return calculations were used to test the profitability of candlestick patterns. The sample is from Thomson DataStream 2019 and IRESS SA 2019 and covers ten years with 2496 observations starting from 02 January 2009 to 31 December 2018.

The findings from the ARCH and GARCH tests revealed that there is a serial correlation between the returns from the previous day and the returns for the current day. The results from the mean returns and the binomial tests show strong evidence that the shooting star, hanging man, bearish engulfing and the bulling engulfing are statistically significant in predicting the share price movements. On the other hand, there was no evidence that the dark cloud cover, piercing lines, and the bullish doji can predict share price movements. Additionally, further studies on this topic could be improved by adding different candlestick patterns and the total number of companies analyzed. The results could also be improved by analyzing the candlestick reversal patterns when they are used with other trading rules such as support resistance levels and oscillators.

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LIST OF ACRONYMS

APN	Aspen Pharmacy Holding
ARCH	Autoregressive Conditional Heteroskedasticity
CPI	Capitec Bank Holding LTD
DSY	Discovery LTD
EMH	Efficient Market Hypothesis
EPS	Earning Per Share
JSE	Johannesburg Stock Exchange
KIO	Kumba Iron Ore LTD
MNP	Mondi PLC
MRP	Mr Price Group LTD
MTN	MTN Group LTD
NPN	Naspers LTD
P/B	Price to Book Ratio
P/E	Price to Earnings Ratio
PEG	Projected Earnings Growth
ROE	Return On Equity
SOL	SASOL LTD
SHP	Shoprite Holdings LTD

CHAPTER ONE

INTRODUCTION

1.1. Background of the Research

There are numerous factors investors need to consider when making investment decisions. "Investment timing" is one of the important factors that investors have to take into consideration when trading. This approach involves making decisions about buying or selling financial assets based on predictions about future market prices (Mankiw, 1997). A well developed financial market suit the needs of lenders and borrowers and the overall economy (Parkin, Powell and Mathews, 2012). When people invest more, they expand their ability to produce more output at a lower cost, which means better productivity and economic expansion (Parkin *et al.,* 2012). According to Mankiw (1997), there is a positive correlation between economic growth and investment.

There are two main classes of assets that investors may use in their portfolios, namely bonds and shares (Elton, Gruber, Brown and Goetzmann, 2014). Share offers a unit of ownership in a company, whereas bonds are loans from investors to the government or companies. In general, shares are considered riskier than bonds (Elton *et al.,* 2014). The issuers of most bonds promise to pay a fixed rate of interest income to investors while the issuer of share may sometimes pay dividends but has no obligation to make these payments (Jones, 2007). How organizations decide to finance their investments, whether through debt or equity instruments is explained by the market timing hypothesis notion. This concept was first introduced by Baker, Taliaferro, and Wurgler (2004). It states that corporations and firms look for a cheaper type of financing and that they do not care if they are financing through debt or equity. Firms look for mispriced securities that seem to be more valued by the financial markets. Nevertheless, the theory itself does not explain why mispricing happens but assumes that it does occur in the market (Baker *et al.,* 2004).

To determine share market timing; when to buy and sell shares, is very complex. The equity market is very volatile and the security prices continually go up and down (Jones, 2007). As the financial markets have become larger and more complex, traders and investors have come to need expert assistance in their investment decision making. Investors can choose to manage their investments from two investment strategies: active or passive (Malkiel, 2003). A passive investment strategy is a strategy that recommends that to maximize return on a portfolio, investors should minimize the frequency of trading (Malkiel, 2003). On the other hand, an active investment strategy is a more hands-on approach (LeBaron, 2011). An active manager strives to beat the market by using different techniques that gauge the financial assets which will yield higher returns.

There are two approaches that an active manager can use when evaluating an asset price especially for spot trading and these are based on technical or fundamental analysis. Fundamental analysis is defined as a technique of measuring a security's intrinsic value by assessing associated economic and financial factors (Zhai, Hsu, and Halgsmuge, 2007). It takes numerous factors that affect the security's value into account, from microeconomic to macroeconomic factors. Technical analysis, on the other hand, seeks to predict future price movement and identifies trends through the study of past market data. It involves making predictions about future prices based on statistical examination of the history of price movement (Zhai *et al.*, 2007).

One of the well-known methodologies of technical analysis is the candlestick approach (Kamo and Dagli, 2009). It originated from Japanese rice merchants and traders who tracked market prices and daily momentum hundreds of years before it became popularized in the United States (Kamo and Dagli, 2009). These days many markets are making use of candlestick patterns as part of their trading system because of its simplicity and easy to use when identifying the market direction (Ameen, 2013).

Despite many being in favor of fundamental or technical analysis, market timing through this process is also controversial. According to the efficient market hypothesis (EMH), technical analysis is based on pure chance and is a form of gambling (Malkiel, 2003:60). The EMH argues that security prices quickly and fully display all information. The information which consists of current and past information about the firms' operation and the economic factors. This means that investors cannot exploit any information that may assist them to sell overvalued or purchase undervalued assets in the market and that the shares on the share exchange trade at their fair value. This, critics argue is due to the complexity of the share market, which can be very volatile and hard to predict (Musah, Senyo and Nuhu, 2014). On the other hand, opponents of the EMH believe that with specialized models one can capture volatility and be able to read the market direction.

Volatility is a statistical measure of changes in returns for a given market index or security. This concept has received a lot of attention from policymakers, academics, and practitioners because it can be used to measure the risk associated with assets (Miah and Rahman, 2016). This topic also received a lot of attention because high volatility on an asset may discourage investors to invest in it. Volatility can also be measured by the variance or standard deviation of the returns from that same asset. The most popular non-linear models that market participants have been using to capture volatility in finance is the generalized autoregressive conditional heteroscedasticity (GARCH) and the autoregressive conditional heteroscedasticity (ARCH) models.

Every investment has different returns and risks. As mentioned earlier, shares and bonds are the most common investment securities. Shares, however, are riskier than bonds. Modern Portfolio Theory (MPT) offers guidance on ways in which risk-averse investors can optimize the return on a portfolio (Elton, 2014). According to MPT, it is possible to have an optimal portfolio that can generate maximum returns at a given level of market risk. The optimal portfolio is constructed through the diversification process. Diversification, which is a risk management strategy, suggests that investors have to mix a variety of securities in their portfolios to reduce risks. The logic behind this theory is that a portfolio formed from a variety of assets will yield higher returns in the long run and by reducing the unsystematic risk on it.

1.2. Problem Statement

The research problem driving research in this field is that to determine the most profitable market timing (when to buy and sell securities), is difficult to achieve. The topic has attracted interest amongst researchers in most developed markets such as the United Kingdom and the United States of America. In South Africa, however, the topic has been underexplored. There is a need to study the potential benefits of market timing in South Africa’s market because it has become larger and more complex during the past decade. The role of market timing on equity returns requires thorough attention. Such research has the potential to add knowledge or provide information to investors which they can use in determining when to go long or short in order to maximize return on investment.

The debate on market timing has remained inconclusive. Many financial professionals, investors, and academics believe that it is possible to outperform the market. On the other hand, proponents of the EMH do not believe in overvalued or undervalued markets and deem market timing as a pure chance which is in the form of gambling; and that financial prices cannot be foreseen with consistency because the market's prices continually display random walk behavior. The market timing topic is important to investors as it touches on the important issues such as returns and risks of an investment. Research in this field provides a resolution to the ongoing debate between active and passive managers. Because the results may provide insight on the performance of the unit trust by testing if the market is efficient or not and therefore investors will be able to make educated decisions on whether to go with a passive or active investment strategy.

1.3. Goals of the Research

The goal of this research is to analyze the earning potential of the South Africa equity market using the candlestick methodology as a market timing technique. In pursuit of this goal, the following sub-goals apply:

1.3.1 To test if historical share prices can explain the future price movement.

1.3.2 To analyze the potential benefits of market timing as part of an active portfolio management strategy.

1.3.3 To establish the probability of being profitable based on the signals from the candlestick pattern.

1.4. Methods, Procedures, Techniques and Ethical Consideration

This study examines daily data for ten years starting from 02 January 2009 to 31 December 2018. The reason for the choice of daily data is because sizable changes in the equity market may occur daily allowing the study to track the development of trends. Lastly, daily data provides enough observations for econometric estimation as suggested by prior studies such as

Fleming, Kirby, and Ostdiek (2001). This research is based on ten companies from the JSE top 40 2019 composition. The sample of the ten companies is stratified based on sector, and market capitalization. The main sources of data are Thomson DataStream (2019) and IRESS SA (2019), previously known as McGregor BFA. This study is quantitative and will analyze the candlestick pattern of a "single line" and "reversal trends" to test if these candlestick patterns can predict share prices. Also, this study assumes that investors were able to purchase shares at the daily closing price.

The binomial test is used to calculate the probability of the candlestick patterns to test if the candlestick signals are statistically significant or not. When the value of the calculated probability is more than 0.5 it indicates that the candlestick patterns can predict security price movement in the short term, otherwise, it is indicating that the candlestick reversal patterns have no value (Tharavanij and Siraprapasiri, 2017). This study tests for the correlation between the past share prices and future share prices using the ARCH and GARCH models. The GARCH and the ARCH models are popular non-linear models in finance which are used for modeling, switching models and to make predictions of the future volatility. And the results from these models will be able to tell us if historical price data can be used to make predictions of future share price movements.

1.5. Outline of the Project

The rest of this paper is organized in the following manner: Chapter 2 discusses the theory underlying market timing and investment return. Chapter 3 provides a revision of existing studies and empirical findings. Chapter 4 details the data used and describes the technical methodologies used in this paper when testing if the candlestick patterns can be used to predict future share prices. Chapter 5 presents the empirical findings and Chapter 6 provides a conclusion of this research and recommendations for future studies.

CHAPTER 2

THEORY UNDERLYING ASSET VALUATION, MARKET TIMING, AND INVESTMENT RETURNS

2.1. Introduction

This chapter describes the concepts underlying asset valuation, investment timing, and market timing. The chapter beggings by further elaborating on the difference between active versus passive investing which was introduced in the previous chapter, followed by the efficient market hypothesis, market timing and then the technical analysis concept.

2.2. Active Versus Passive Investing

As indicated in the previous chapter, there are two main investment strategies followed by individuals and/or fund managers; passive and active investment management (Malkiel, 2003). Both of these strive to achieve maximum investment returns. A passive strategy is one in which the frequency of trading is minimized (Malkiel, 2003). This is also known as the "buy and hold strategy" because investors buy securities and hold them for long periods despite short-term changes in the market. This also reduces trading costs (LeBaron, 2011). A typical approach is to buy units in an investment fund based on a representative benchmark or market index (LeBaron, 2011).

In contrast, the active investment strategy is a more hands-on approach, which strives to beat the market (LeBaron, 2011). Active managers attempt to acquire maximum portfolio returns by using a variety of techniques to buy and sell individual assets (shares) which are expected to yield higher returns than the overall market. Active management could be based on technical or fundamental analysis or a combination of both. In technical analysis, which is the topic of this study, the main approach is the exclusive use of historical price and volume data. This is what separates the technique from its fundamental counterparts. Unlike fundamental analysts, technical analysts do not primarily concern themselves with the fundamental or theoretical determinants of a share's valuation. The main factor that matters is past trading data and what information the data might provide about the expected future price movements (Levy, 1966).

The counterargument is based on the Efficient Market Hypothesis (EMH), which in its strongest form states that a share price already reflects or includes all market information that could affect a company. This includes fundamental factors (Malkiel, 2003). Technical analysts believe that everything from a company's fundamentals to broad market factors to market psychology is already priced into the share (Malkiel, 2003). This removes the need to consider the factors separately before making an investment decision. The only factor remaining is the analysis of price movements, which technical analysts view as the product of supply and demand for a particular share in the market (Malkiel, 2003).

2.3. The Efficient Market Hypothesis (EMH).

One of the ground-breaking themes in the literature since the 1960s has been the concept of an efficient capital market (Malkiel and Fama, 1970). In the field of finance, the term "efficiency" has a very specific meaning, i.e. that security prices fully reflect all available information (Elton *et al.*, 2014: 412). Linked to the rational expectations approach, the EMH also assumes that security prices would fully incorporate and display relevant information (Delcey, 2018).

The theory is relevant for investment management because it involves a guide to expectations about the potential for profitable trading, in particular, the likelihood of finding a fund manager or agent who can beat the market. Underlying the EMH is the concept of the invisible hand of the marketplace (Elton *et al.*, 2014: 410). Competition among traders in the market to buy undervalued assets and sell overpriced assets will quickly eliminate gains to zero.

The EMH is also rooted in the random walk hypothesis (Mandelrot, 1963; Samuelson, 1965). In it, it was noted that the EMH implies only that "the market quotation … already contains in itself all that can be known about the future and in that sense has discounted future contingencies as much as humanly possible" (Samuelson, 1965, in Elton *et al.*, 2014: 411). Future prices must, therefore, be based on information available at the time prices are established and speculation (market timing) comes down to a "fair game" with an expected reward of zero.

The information dealt with by the EMH has different dimensions. There is current and past information, but it also needs to be considered whether the information is privately (within the company) or publicly available. Such information affects firms' operations. If the EMH holds, it means investors cannot exploit any information that may assist them to sell overvalued or purchase undervalued assets in the market. Shares, therefore, trade at their fair value. The EMH is categorized into three forms: the weak, semi-strong and the strong form.

- The weak form proposes that past information is included in the price of a security. In this form, it is believed that the fundamental analysis of securities may provide information in the short run that an investor can use to produce returns that are above the average returns in the market. However, the fundamental analysis does not provide advantages in the long run and there are no “patterns” which can be used to explain the market direction, therefore technical analysis does not work in the weak form of the EMH.
- The semi-strong form implies that all publicly available information is fully reflected in the share price. This implies that no trader has any kind of informational advantage in the security markets. The use of technical analysis or fundamental analysis cannot provide an advantage to an investor because when new information comes out it is instantly incorporated into the process of the pricing of security.
- The strong form of the EMH states that private and public information is priced in the security and that investors cannot make returns greater than the returns acquired from the market as a whole.

Active investors claim that they can predict the share prices by estimating the expected cash flow from the share and the risk assigned to it. Active managers also claim that the EMH failed to explain the share market behavior because it assumes that everyone in the market obtains all available information in the same manner. However, this assumption poses some problems for its practicality. If some investors search for undervalued asset opportunities while some search for growth potential, these investors will have different valuations of the asset’s fair market value (Jones, 2007)

2.4. Market Timing

Market timing is a trading strategy that involves decisions about switching between individual assets (such as shares) or between asset classes and going in and out of the financial markets. It comprises using economic data or technical indicators to project the future price movements of securities. Whether market timing is a viable investment strategy has been an ongoing debate between investors. Many financial professionals, investors, and academics believe that it is possible to outperform the market. On the other hand, the above section indicated that proponents of the EMH do not believe in overvalued or undervalued markets and deem market timing as pure chance which is nothing more than a form of gambling; and that financial prices cannot be foreseen with consistency because the market's prices continually display random walk behavior. This is discussed further in the following three chapters. The rest of this chapter will discuss different theories, methodologies, and techniques for market timing which will be divided into two parts; fundamental and technical analysis.

2.4.1. Fundamental Analysis

Fundamental analysis is an approach of measuring a security's intrinsic value by assessing associated economic and financial factors (Dingile, 2017). It takes numerous factors that affect the security's value into account, ranging from microeconomic to macroeconomic factors. Microeconomic factors include variables internal to the company such as management style, market share, innovation, etc. Macroeconomic factors are variables relevant to the business and industry conditions, as well as the overall macroeconomic indicators relating to the overall economy, domestic as well as global.

The end goal of using fundamental analysis is to quantify the current worth of the security so that investors can assess if it is valued correctly within the broader market (Dingile, 2017). Investors would then take the intrinsic value from using fundamental analytical tools and compare it with the current security market price to test whether the security is overvalued or undervalued. If the current market price is lower than the intrinsic value the security is thought to be undervalued and the investor would benefit from buying the security. In the opposite case, the security would be overvalued and the investor would be better off by selling it (Bassetti, 2018).

Fundamental analysis is commonly used for evaluating share prices (Dingile, 2017). However, it is also useful for valuing other asset classes such as bonds or derivatives. Fundamental analysis is performed based on the historical and current financial information available of a company (Dingile, 2017). When valuing shares, investors use data from earnings, expected future growth, profit margins, return on equity and other data which determine a firm's future growth and its underlying value. All this data can be found from the firm's financial statements (Dingile, 2017). Fundamental factors can be divided into two classifications: a qualitative and quantitative analysis. The quantitative factors measure the intrinsic value in terms of numerical values and qualitative factors express the corresponding value in terms of non-numerical value

(Park and Irwin, 2007). Many analysts believe that neither quantitative nor qualitative is really efficient on its own, but the combination of the two usually acquires the desired results (Park and Irwin, 2007).

Fundamental analysis has numerous tools used to compare and evaluate securities. After all, the most important decision the investor can make before buying shares is to choose a company of good value and good quality (Dingile, 2017). Individuals who mainly use fundamental analysis to pick shares normally use a range of tools to make these decisions. Fundamental analysis tools include indicators and ratios (Jones, 2007). These ratios are not difficult to calculate and most of them are already available. The most common ones are centered on growth, earning and value in the market (Jones, 2007). Popular ratios of fundamental analysis include: earning per share (EPS), price to earnings ratio (P/E), projected earnings growth (PEG), price to book ratio (P/B), dividend payout ratio, dividend yield and the return on equity (ROE) (Jones, 2007).

- The EPS measures the amount of Rands earned per share. EPS is calculated by subtracting preferred dividends from net income, divided by the number of outstanding shares.
- The P/E ratio gives information on whether the company is undervalued or overvalued. The P/E ratio is calculated as the share price divided by earning per share.
- The PEG ratio gives the shares' value while factoring in the company expected earnings growth. The PEG is believed to provide more complete information than the P/E ratio. The formula of the PEG is given by price-earnings divided by the annual earnings per share growth rate.
- The P/S compares the firm's share price to its revenues. P/S ratio is calculated by the company's market capitalization divided by the revenue of the most recent years.
- The P/B ratio is used to compare a company's market to book value by dividing the price per share by book value per share.
- The dividend pay-out ratio is a fraction of dividends paid to shareholders by the net income of the company. This ratio tells us the amount that is retained by the firm that may be used to reinvest in core operations or be used to pay off debt.
- The Dividend yield compares yearly dividends to the share price and is expressed as a fraction of annual dividend per share by market value per share.
- The ROE is a measure of a company's profitability in relation to equity. ROE is calculated as a fraction of average shareholders' equity by net income.

2.3.1.1 The Arbitrage Pricing Theory (APT)

A popular framework for analyzing security prices is the arbitrage pricing theory. The APT is a multi-factor technical model centered on the relationship between a financial asset's anticipated risk and return. This model was developed in the 1970s by Stephen Ross. The APT is based on three assumptions: firstly, expected asset return can be explained by systematic indicators. Secondly, investors can eliminate specific risks by diversifying their portfolios. Lastly, in a well-diversified portfolio, there are no arbitrage opportunities. The principle behind the APT is that the return on an asset can be explained by assessing two factors: 1) macroeconomic influences or indicators and 2) a share price's sensitivity to such influences (Ross, 1970). This technique is intended to detect the sensitivity of the security's returns to variations in macroeconomic indicators. Financial analysts and investors will then use these results when making decisions and when pricing an asset.

The APT establishes that the long-term average return on an asset is based on a few systematic indicators (Ross and Roll, 1980: 33). Systematic factors represent the main causes of risk in portfolio returns. These factors are defined as the major effects that move the share price (Ross and Roll, 1980: 33). However, the APT does not reject that there are many additional factors that could cause daily price fluctuations on shares. Such additional variables may be influences that are not systematic to the whole economy and hence termed "idiosyncratic" (Ross and Roll, 1980: 33). The idiosyncratic influences are distinguished from the systematic factors because the latter describe the main movements of portfolio returns.

The APT focuses on systematic factors because through the process of diversification the idiosyncratic effects cancel out. Large portfolios are therefore mainly influenced by systematic factors alone (Ross, 1980: 9). The basic arbitrage pricing theory formula is:

$$E(R_p) = R_f + ß_1 f_1 + ß_2 f_2 + ß_3 f_3 + \ldots + ß_n f_n + e_i \quad \text{(2.1)}$$

where: $E(R_p)$ = the expected return on the asset

$R_{f,}$ = the risk-free return (usually on government bonds)

$ß_n$ = Sensitivity of the asset's return to the systematic factor

f_n = Systematic factor for n^{th} term

e_i = Idiosyncratic factors (Error term)

The APT shows that the expected return on shares is a linear function of the asset's sensitivities to the *n* factors. There is no general set of macroeconomic factors that are used in the APT for any given security. Instead, these factors are different for each security or each market and need to be specified. The beta coefficient ($ß_n$) is a measure of risk or sensitivity of an asset's return or price to changes in each factor. Under the APT there is a range of betas, each giving the return's sensitivity to that factor. The larger the value of the $ß_n$, the more sensitive the return of the security is to changes in that specific macroeconomic factor (Ross, 1980: 9). In addition, if the sign accompanying the $ß_n$ is positive, it means that the return of the security and the macroeconomic factor share a positive relationship. In contrast, if the sign is negative, the expected return and the macroeconomic factor have an inverse relationship.

2.3.1.2. The Capital Asset Pricing Model (CAPM)

The CAPM is an alternative to the arbitrage pricing theory. It was introduced by Lintner, Sharpe, and Mossin (Reinganum, 1981). The CAPM gives is the relationship between the expected return of an asset and the systematic risks for security, particularly shares. As will be shown below, the main difference between the above APT and the CAPM is that the risk of the asset in the CAPM is measured only against the market as a whole, as compared to the APT, which measures it against a range of factors. The objective of this model is to assess if an asset is fairly valued when the time value of money (interest rate) and the asset's risk relative to the market as a whole are taken into account (Reinganum, 1981). It is extensively used in finance for estimating the expected returns on risky assets. The CAPM is based on the following assumptions:

- Investors are risk-averse. When investors are exposed to the uncertainty in the market they try to reduce that uncertainty. A way to achieve this is to diversify asset holdings.
- Investors endeavor to maximize the return on their assets and therefore maximize their wealth. As such, they focus on increasing the utility obtained from their wealth.
- Investment decisions are based on return and risk. The CAPM assumes that investors make decisions based on return and risk. Return is normally measured by the mean return over time. Risk is typically quantified by the variance of the returns over time.

- Investors have similar expectations of return and risk. They evaluate return and risk in the same manner. Therefore all investors also have very similar expectations of return and risk.
- The same time horizon applies. The CAPM assumes that all investors buy securities at one point of time and sell them at some common point in the future.
- All information is publicly available. This is one of the key assumptions of the model. The practical implication is that all information needed by investors to make decisions is freely available at no cost.
- There is no limitation on lending and borrowing under the risk-free asset. This refers to a situation where unlimited borrowing and lending is possible under conditions of no risk, such as making use of government bonds.
- There are no transaction costs and taxes.
- All securities are marketable and the number of availability of assets is fixed. Under this assumption, the supply of assets/shares (particularly in the short-term) is fixed and all assets can be sold in the market.

Now to move on to the specific formulation of the CAPM. The CAPM specifies the expected return on an asset as a linear function of the risk-free return and a risk factor relative to the market as a whole. This is given in Equation 2.2:

$$E(r_i)= r_f + ß_i*(E(r_M)-r_f) \qquad (2.2)$$

Where $E(r_i)$= Expected return on asset

r_f = Risk-free return

$ß_i$ = Beta of the security

r_M = Expected market return

Beta (ß) is a key factor in the CAPM model and is a measure of the volatility of the returns of the asset compared to the market. A typical benchmark for the value of ß is 1. When larger than 1, it indicates that the particular shares carry a higher risk profile than the market as a whole (Reinganum, 1981). One of the limitations of the CAPM is that most of its assumptions do not hold in reality (Goetzmann, 2009). The CAPM requires the collection of data on all assets in the market to estimate the expected market return. Therefore, without the global portfolio data, it is difficult to conduct the CAPM test. Even the studies conducted using the data from the global publisher for portfolio information Standard and Poor’s (S & P) did not really produce satisfactory results because the information was insufficient for estimating the CAPM model (Goetzmann, 2009).

Some of the main differences between the models are now given briefly. First, The APT does not assume that the investor holds efficient portfolios. The APT also does not state which factors should be used in the model. Each researcher would construct the equation for the particular asset under investigation. As such, APT users must determine the relevant indicators that influence the return on an asset (Lintner *et al.,* 1965). In the case of the CAPM, a crucial element is to determine the relationship between the expected return of an asset and the risk-free return. This is normally determined by a market risk premium. Another difference between the models is that the CAPM consists of nine assumptions whereas the APT has only three main assumptions. Both being linear, the CAPM and APT formulas appear similar, but the CAPM only has one beta (the risk of the asset's return relative to the market as a whole) and therefore one factor, whereas APT has several betas and several factors (Ross and Roll, 1980). In addition to this, the most committed supporters of the CAPM also admitted that it is not easy to fit the CAPM model in reality (Goetzmann, 2009). Consequently, the APT is seen by many as the best existing model for estimating a return on shares.

2.5 Technical Analysis

Technical analysis is regularly taken to be the opposed approach to fundamental analysis. "The technical approach to investing is essentially a reflection of the idea that prices move in trends which are determined by the changing attitudes of investors toward a variety of economic, monetary, political and psychological forces. The art of technical analysis is to identify trend changes at an early stage and to maintain an investment posture until the weight of the evidence indicates that the trend is reversed" (Pring, 1991). Technical analysis is formulated from published data such as sales, earnings, government regulations or growth rate (Jones, 2007:433). Technical analysts believe that "the market tells its own story", which means that the market on its own is the greatest source of data. On the other hand, fundamental analysis is centered on political and economic determining factors.

Technical analysis consists of different tools that investors can use when reading a market's direction. Traders want to know the best tool that is efficient in forecasting the asset's price, and the answer to this question could save them effort and a lot of time. Unfortunately, there is no straightforward recipe. People have different views on which technical analysis tools are more useful. This is because each investor or trader strives to discover a methodology that fits his/her talent and benefits (Jones, 2007). A successful methodology for one investor may be a losing strategy and a poor fit for another investor. The paragraphs below discuss technical analysis tools.

2.5.1. The Dow Theory

The Dow Theory is the oldest and most well-known theory of technical analysis. It was originally established by Charles H. Dow the editor of *The Wall Street Journal* in the late 1800s. Many academics honor Charles H. Dow as the father of technical analysis. This theory was very common in the 1920s and 1930s and articles providing support for it still emerges occasionally in the literature (Jones, 2007:435). It is an approach to describe market movements. Following Charles H. Dow; Robert Rhea, William Peter Hamilton and George Schaefer structured and collectively represented Dow theory and come up with six basic principles based on Dow's editorials. These principles are:

- The share market discounts all the news. This principle states that share prices immediately integrate all information as soon as it becomes available in the market. This information consists of data such as changes in the rate of inflation, earnings announcements by companies and investor sentiment, to name a few.
- The market is driven by three main trends. Firstly, the primary movement which is a general market movement that survives for several years. Secondly, the intermediate (secondary) movement which occurs within the primary movement, and this represents disruptions that last for a few weeks or months. Thirdly, day-to-day fluctuations, which happen at random between the primary and the secondary movements.
- Trends have three phases. The theory states that there are three identifiable phases at work in the major market trends: an accumulation phase, the public participation phase, and the distribution phase. In the accumulation phase, investors are actively buying and selling shares despite the general opinion in the market. During this phase, investors are looking for shares that the market at large is providing. In this phase share prices usually do not change much. In the public participating phase other investors join the market as business conditions advance. This causes higher prices in the market. The final phase is the panic phase when the market is characterized by the extreme selling of securities by investors.

This could lead to significant speculation. At this point, investors would benefit by leaving the market (Jones, 2007).

- Indices confirm each other or tell the same story. This means that a trend should not be branded and tested by one index alone. A variety of indices should confirm a particular opinion. For example, in the case of South Africa if there is a bullish trend, then the FTSE/JSE Alt X Index, all share index, FTSE Fledgling index and other indices should be moving in concert in the increasing direction.
- Trends are confirmed by volume. Dow believed that the trend in the market occurs regardless of any noise that might exist in the market. For example, in a downward trend, the volume is increasing with a decrease in price and decreases with an increase in price. And in an upward trend, the volume increases with a rise in price and decreases with a fall in prices.
- The trend continues until definitive signals indicate that they have ended. Dow believed that the market trend exists irrespective of the market noise. That is the market might temporarily move in the opposite direction to the trend, but they will soon return to the prior move.

Even though the Dow Theory was developed a hundred years ago, the theory is still used in the current trading market. The theory is intended to forecast price movements, but it does not provide information on how long the expected trend would persist. Nevertheless, the Dow theory is subject to many criticisms and studies on its achievement rate have been unsatisfactory. A major problem with this theory is that there exist many versions comprising of numerous investment letters. Therefore, Dow Theory users understand the theory in different ways. Consequently, investors using this theory may predict different movements at the same time (Jones, 2007:436).

2.5.2 Price Patterns and Charts

Charts are graphical representations of data that can be represented by a form of symbols, such as bar charts, line charts or pie charts (Jones, 2007). Technical analysts are confident that share prices move with price changes creating patterns that can be categorized and recognized visually by evaluating the forces of demand and supply (Kamo and Dangli 2009). Technicians usually rely on graphs or charts to analyze individual share price movements. Technical analysts intend to detect certain signals in a share price chart and make use of terminologies to explain the event. The basic terminologies are the resistant level and the supporting level. The so-called “resistant level” is the price range at which chartists anticipate prices to be at the upper bound of the trend or cycle and an increase in the supply of the share is expected (Kamo and Dangli 2009). On the other hand, the “support level” is the price range in the trend where analysts expect the price to be at the lower bond and therefore anticipate an increase in the demand of shares. Each chart has its benefits and limitations, as will be discussed in more detail in the following paragraphs.

- Line charts: a line chart is the simplest type of charting. Most people's first encounter with charts is with the line chart. The line chart consists of two variables; the price and the time, in most cases the price is the closing price. The line chart is also the most common measure of share price movement, which shows the movement of the share price. When the demand for shares is rising more than the supply, the share market is in an upward trend. A downward trend occurs when the supply of a share is increasing more than the demand for it. Consequently, investors would wish to sell in a downward trend and buy in an upward trend. Before the introduction of personal computers, many technician experts drew charts by hand. The line chart became popular because of its benefit of being easy to construct (Kamo and Dangli 2009). To draw the line chart, one should use each day’s closing share price. Chartists draw a visual representation of shares and believe they are able to use the trend to predict the future price movement (Jones, 2007). Regardless of the wide variety of charts and trading tools available; line charts are still popular. These days’ line charts are mostly used to compare two or more indices or share performance (Kamo and Dangli 2009).
- Bar charts: most technician experts believe that a single price is not enough. For example, if one is to focus on the closing price only, there will be no information about what took place before (Kamo and Dangli 2009). Using the line chart will not tell if the price drifted before the close. Thus, the use of a line chart omits material information. Therefore, the implementation of bar charts brings the solution to the line chart limitations. The bar charts comprise of the low, high, opening and closing price and are plotted with the time period on the horizontal axis and the price on the vertical axis. The lowest price is represented by the lowest point of the bar. In contrast, the highest point of the bar shows the highest price reached during a certain period. A short bar shows that the price comprises of a tightened trading range, and a tall bar denotes a broad trading range.

- Candlestick charts: one of the well-known methodologies of technical analysis is the candlestick approach (Kamo and Dangli 2009). Like bar charts, candlestick charts are employed to display the high, low, opening and closing prices of a security for a specific period. It originated from Japanese rice merchants and traders to track market prices and daily momentum hundreds of years before becoming popularized in the United States (Kamo and Dangli 2009). A black candlestick shows that the closing price was lower than the opening price. This is bearish and investors should sell shares. On the other hand, a white candlestick indicates that the closing price was more than the opening price; hence, it is bullish, and it indicates buying pressure. A "White Marubozu" is a single line or daily candlestick that suggests the continuation of a price increase because the price opened at the day's low and rose throughout the day to close at the day's high (Garcia and Gencay, 2003). A "White Marubozu" indicates a case where buyers are more than sellers and bid up prices during the day. The odds are that the prices will continue to increase due to the supply/demand imbalances. Furthermore, successive single lines can form a continuation and reversal pattern. A continuation pattern shows that the prevailing trend is expected to continue, meanwhile a reversal pattern indicates that the trend is expected to change, thus providing the investor with the buy or sell signals (Garcia and Gencay, 2003).
- Point and figure charts: point and figure (P&F) charts are a technical analysis technique that plots the price changes for securities without taking into consideration the track of time. They are therefore unlike charts such as candlesticks that plot the securities' movement over a set period. The P&F makes use of columns with stacked Os or Xs. Each Os or Xs represent the amount of price movement. The Os denotes a decrease in price and the Xs represent an increase in prices. The P&F is designed to condense price movements into a small area. By compressing price changes the area of congestion can be identified. Technical analysts study and search for "breakout" by analyzing the congestion area, which provides direction to whether a share price will be increasing or decreasing. However, P&F has drawbacks and one of them is that it only shows price changes without any information on volume changes (Kamo and Dangli 2009).

2.5.3 Moving Averages

The moving average is a simple and widely used tool in technical analysis (Post and Levy, 2005). The moving average helps to smooth out the historical price trend by making the short term price fluctuations less visible. This technique is used when analyzing the rate of change or the direction of individual share and the overall market. The moving average is constructed from the closing price. There are three major decisions to consider when composing the moving average and in each of the decisions there exist several alternatives.

- The time frame over which the moving average is calculated. This involves deciding on the time frame of which the moving average is calculated. This step is important because the selected time frame can influence the overall moving average. A common time period for identifying trends is 200 days. Alternatively, shorter time periods may also be used.
- The price used. Generally, the closing prices are used in constructing the moving average. However, sometimes the low, high, opening and closing prices are used in different configurations.
- The type of moving average: Technical analysts can use a simple moving average, exponential or weighted average. Simple or linear moving averages use equal weights on each day's price activity, and the exponential and weighted averages place a higher weight on the most recent price activities (Post and Levy, 2005).

2.5.4. Relative Strength

Relative strength is a popular technique used when analyzing individual share prices. It is calculated as the ratio of a share's price relative to the industry index (Jones, 2007). It is also calculated as the share price average over some previous period or as the ratio of an industry average relative to the market (Jones, 2007). These ratios can be displayed in the form of a graph of relative prices over time. The outcome of the graph displays the strength of the share relative to its industry in the market. Relative strength is used to forecast share prices over time. An increasing line during the construction of the relative strength is perceived to indicate that the share is outperforming the industry and that it may continue to do so (Jones, 2007:443). A declining ratio is represented by a downward slope line and it suggests that the share is underperforming the market. The rule of thumb when using this technique is that a share is attractive when the relative strength has improved for at least four months (Jones, 2007:443).

2.5.5. The Use of Computers in Technical Analysis.

Before the introduction of computers, investors used to draw charts themselves or pay for a service that supplies hard copies of charts (Jones, 2007). Nowadays investors can buy a wide range of software with data and programs on it or may choose to use an online service. The online services provide any type of trading system, but it does not allow for historical backtesting. The software-based programs provide the user with multiple technical indicators and a backtest to the system. Using computers in technical analysis requires both data and program vendors, and may be expensive. However, most users find the use of computers (online services or software-based programs) sufficient because technology has changed the information platform and the way information now circulates and is transmitted is a lot quicker, transparent and accessible (Jones, 2007:444).

2.5.6. ARCH and GARCH

To empirically test the profitability of market timing, technical analysis tools need to be supplemented by measures of volatility testing. This chapter is therefore concluded with a short section, from a theoretical perspective, of the common models that are used to analyze time-series data. The ones employed in this study are the ARCH and GARCH models. The ARCH stands for autoregressive conditional heteroskedasticity and the GARCH stands for generalized autoregressive conditional heteroskedasticity. The original studies of these models field were done by Bollerslev (1986) and Engle (1982) who proposed the GARCH and ARCH models respectively. The ARCH/GARCH models are used to analyze various types of financial data such as macroeconomic data (Engle, 2001).

Financial institutions mostly use these models to forecast the volatility of the returns on bonds, stocks and market indices. This information is useful to identify securities that could potentially generate higher returns as well as to provide them with information that provides guidance when hedging, allocating assets and managing risks on assets (Engle, 2001). The GARCH model consists of three general steps. The first step is to estimate the best fitting autoregressive model. The second step involves computing autocorrelations of the error term and the final step is to test for significance (Engle, 2001).

Seeing that the models are employed in the empirical section of the study, they are described in more detail in Chapter 4 (under section 4.5). Existing empirical findings from the use of ARCH/GARCH in general, are covered in Chapter 3.

2.6. Summary

This chapter illustrates that there are opposing theories in finance that underpin investment management. The viability of market timing is governed theoretically by fundamental and technical analysis. There are also supporters of the EMH, who argue that it is pointless to forecast prices by using technical or fundamental analysis. However, the legitimacy of this hypothesis is controversial. This is so because some investors have successfully beaten the market over the long-term with fundamental and technical strategies. Most investors believe that the rewards that the investor who can read the share market correctly can realize high returns, but the consequences from dozing or careless investors could be highly negative (Edwards *et al.*, 2018). This is the reason why this topic has caught the eye of some of the world's most sharp researchers, accountants and analysts along with a multitude of ordinary citizens who are looking for a sure and safe method for predicting the market movements.

The existing empirical findings from studies that employed technical analysis procedures are covered in the next chapter.

CHAPTER 3

EMPIRICAL LITERATURE REVIEW

3.1. Introduction

The measurement of volatility or risk on securities has become very important in recent decades. That led academics and researchers to develop and use statistical and mathematical models to quantify the volatility of securities' returns. To comprehend the methodologies, procedures, and theories in this topic. This section provides a concise review of existing empirical findings, both locally and internationally. Firstly, the chapter starts by providing a revision on existing studies on the use of candlestick patterns and then discusses existing literature on the ARCH and GARCH models in modeling volatility. Finally, the existing literature on passive versus active management and the efficient market hypothesis is discussed.

3.2. The Use of Technical Analysis in Market Timing

The profitability of the candlestick patterns for a holding period of 1, 3, 5, and 10 days was examined by Tharavanij, Siraprapasiri, and Rajchamaha (2017). Two exit strategies were analyzed, the Gaginalp-Laurent (CL) and the Marshall-Young-Rose (MYR) approaches. The paper examined data over 10 years from July 2006 to June 2016. The data used include low, high, opening and closing prices for the top 50 capitalization shares on the share exchange of Thailand. The goal for this research was to assess the forecasting power of the bearish and bullish candlestick reversal patterns with and without technical filtering by implementing the binomial test and the skewness from the adjusted t-test. The results found that there was little use of both bearish and bullish candlestick reversal patterns because the mean returns were not statistically different from zero for most patterns. The binomial test findings suggest that candlestick patterns do not predict market prices accurately (Tharavanij *et al.,* 2007).

The studies which tested if the hedge funds in the United States have the capability of timing the equity market using the squared sharp ratio and bootstrap analysis were conducted by Cheng and Liang (2007) and Marshall, Young and Rose (2006). The bootstrap analysis was used to evaluate descriptive statistics on the dataset (Marshall, *et al.,* 2006:2305). The Sharpe ratio was used to compare the return and risk of investment (Marshall, *et al.,* 2006). According to Cheng, *et al.,* (2007), the squared Sharp ratio was able to time the equity market and the results from the bootstrap analysis support the view that the evidence was not indorsed by luck.

The profitability of four bearish and four bullish candlestick reversal patterns was examined using seven foreign exchange currencies (Ameen, 2013). The currencies evaluated were the United States Dollar per Canada Dollar, British Pound per United States Dollar, Euro per United States Dollar, Australian Dollar per United States Dollar, United States Dollar per Japanese Yen, United States Dollar per Indian Rupee and United States Dollar per South African Rand. The sample covered 3129 observations for 12 years. The statistical significance of the returns was tested at a 5% level using the statistical Z score test for seven holding periods. For an additional filter of the results, the RSL was utilized with three candlesticks patterns. The findings indicated that there was strong evidence that in some foreign currency markets candlestick reversal patterns were profitable (Ameen, 2013).

Do Prado, Fernada, Luiz, and Matsura (2013), tested the efficiency of candlestick patterns in predicting share prices in Brazil. This was done by calculating the returns acquired from the use of candlestick patterns and comparing them to the buy and hold strategy. This study was done using sixteen different candlestick patterns and ten shares from the Brazilian equity market for a period of five years starting from 2005 to 2009. The empirical results showed that some patterns confirmed to have predictive powers and therefore can forecast future share prices. A similar study to the one done by Do Prado (2013) was also based on the Brazilian market and it was conducted by Maia and Rodrigues (2018). These researchers used the bearish and bullish candlestick patterns to identify the sell and buy signals. The study covered a period of eleven years starting from 2005 to 2016 and the statistical significance was tested using the Monte Carlo simulation, Skewness, t-test, Z-score, and Kurtosis. The results from these tests revealed that the bullish candlesticks can predict the market price movement.

To test if the Japanese trading technique can function in the European share market. Lu and Cheng (2013) utilize a fourteen vector to categorize two-day candlestick patterns systematically using the bootstrapping methodology. The data used was CAC 40, FTSE 100 and DAX 30 component shares. The results found that candlestick patterns had predictive power and may generate profit for investors after transaction costs have been taken into account.

Ansary and Atuea (2017) analyzed the effectiveness of using the buy and sell signals from the three common technical analysis strategies. The return from the technical analysis strategy was then compared with the buy and hold strategy. The data used in this study is based on the Egyptian security market for the period starting from 1 January 1998 to 14 January 2016. The methodology used is the Wilcoxon/mann-Whitney test and the bootstrap analysis. The results found that technical analysis strategy was more profitable than the buy and hold strategy and that the use of technical tools can reduce risk and increase returns on investments.

When analyzing the application of the candlestick trading strategy Goo, Chen and Chang (2007) used daily data of 25 components shares from the Taiwan Mid-Cap 100 Tracker fund and the Taiwan Top 50 Tracker for the period 1997 to 2006. The methodologies used are the t-tests, ANOVA and Duncan's multiple range test. The t-tests were used to test the profitability of the candlesticks. ANOVA and Duncan's tests were used to compare and examine the profitability of candlesticks patterns. The results provide strong evidence that investors may benefit from using the candlestick trading method. Goo *et al.,* (2007) also discovered that candlestick performance can be improved by implementing a stop-loss strategy. In addition to this, they also discovered that different candlestick should have different holding days.

Caginalp and Laurent (1998) examined the predictive power of candlestick patterns using daily prices of all S&P 500 shares for a period of 4 years from 1992 to 1996. The paper used the out-of-sample and non-parametric tests. The findings from the out-of-sample test showed a statistical significance of the predictive power of the candlestick pattern and suggest that there is a profit of 1% in two-day holding time. The results from the non-parametric test with the use of the three-day candlestick patterns indicated that investors are influenced by the price movements.

The effectiveness of the Japanese candlestick was tested using the neural network (Jasemi, Kimiagari, and Memarian, 2011). The study was done in Iran based on published daily data on Yahoo and the results showed that the neural network and the Japanese candlesticks work well in providing the buy and sell signals. However, the neural network together with candlestick was found to be much better in forecasting share prices than the use of candlesticks patterns on their own.

In Taiwan Shiu and Lu (2011) conducted research intended to investigate the ability of two-day patterns of the candlestick in forecasting price movement. The research used the Quantile Regression Model with data timeframe from 1998 to 2007. The findings of this paper showed that the harami patterns can predict future price movements.

Duvinage, Mazza, and Petitjean (2011) studied the forecasting ability of candlesticks pattern in predicting share prices in Hong Kong share markets. The methodology used is the multiple classifier systems (MCS) and data was based on 40 shares in the Hong Kong Hang Seng Component Index. The results show that candlesticks can predict future shares prices in the Hong Kong market. In 2013 these researchers did another research on this topic were they generated a trading system and market timing strategy to test the predictive power of intra-day of Japanese candlesticks on 30 components of the Dow Jones Industrial Average at 5 minutes interval. It was discovered that at the conservative Bonferroni level about 75% of the candlesticks' rules do better than the buy-and-hold strategy. However, after considering trading costs only a few candlestick patterns remained profitable. To correct for data snooping they implemented the SSPA test and the results with the SSPA test found that no single candlestick could outperform the buy-and-hold strategy after adjusting for trading costs (Duvinage *et al.,* 2013).

Goswami *et al.,* (2009) analyzed candlestick patterns to test if they can predict short term share price fluctuation in the Indian equity market. The data used was from the SOM-CBR. Goswami *et al.,* (2009) discovered that the candlestick patterns are useful and can predict share prices in the short term.

3.3. GARCH in Modeling Volatility

The paper which used GARCH models to estimate the conditional variance for Sudan Khartoum Stock Exchange (KSE) was done by Ahmed and Suliman (2011). The study analyzed the KSE daily data for a period of 5 years, starting from January 2006 to November 2010. The models comprise of both asymmetric and symmetric models that include common stylized facts about index return such as leverage effect and volatility clustering. The empirical results provided evidence that the symmetric model is a better fit than the asymmetric models and the conditional variance process is persistent; which provides evidence that the KSE index return has a positive correlation between expected share return and volatility.

The predicting power of different GARCH models on the S&P-500 share index for the period 01 January 1990 to 28 September 2001 was tested by Awartani and Corradi (2005). To do this a pairwise comparison of different models was performed using the GARCH models. Finally, all models were joined and compared against the GARCH (1, 1) model. The findings reveal that in the case of pairwise comparison, GARCH (1, 1) was outperformed by the asymmetric GARCH models and a similar outcome also applied to various longer forecast horizons. In the joint comparison case, they found that the GARCH (1, 1) model was outperformed by the class of symmetric GARCH, however, it was not outperformed by other GARCH models which do not follow asymmetries.

A study conducted by Arowolo (2013), concentrated on the predictive properties of the Linear GARCH model. This study was based on the Nigerian Stock Exchange focusing on Zenith Bank plc. The study made use of the closing prices for Zenith Bank plc and the methodology used to acquire the order of the GARCH (p, q) was the Bayesian and the Akaike Information Criteria. GARCH (1, 2) was identified as the best fit model. The results found that financial data are Leptokurtic. Arowolo (2013), therefore concluded that the order of the GARCH (p, q) model depends on the types of data and the location and the model selection.

When investigating and searching for a perfect fit for the GARCH model to estimate the Shanghai Share Exchange (SSE) and Bombay Share Exchange (BSE) conditional market volatility. Tripathy and Rahman (2013) used daily closing values of the Shanghai and Sensex

Stock Exchange Composite Index. The empirical findings showed that both SSE and BSE had significant ARCH effects, and it is suitable to use the GARCH model.

Zawali, Safiih, and Anthea (2011) investigated the proposed model which is GARCH (1,1) together with bootstrap percentiles in predicting movements on Kuala Lumpur Shariah Index (KLSI). The paper used daily return data for the KLSL for the year 2009. The study was performed using two steps. The first step was using the GARCH (1, 1) model and the second step was to consider bootstrap analysis with two replications. The effectiveness of the models was tested using the confidence intervals. The results revealed that the proposed model (GARCH (1, 1)) was better in estimating the conditional variance in the short term. Therefore, the proposed model is statistically suitable for estimating the movements of the KLSI data.

The GARCH models were analyzed when modeling the movement of the share markets return for Turkey and the four European countries which were considered emerging markets in finance (Ugurlu, Thalassinos and Maratoglu, 2014). Daily data from the Czech Republic (PX), Bulgaria (SOFIX), Hungary (BUX), Poland (WIG) and Turkey (XU100) were used. The results revealed that EGARCH, GJR-GARCH, and GARCH effects were significant in explaining the returns of BUX, PX, XU, and WIG. On the other hand, the GARCH model was found to have no significance in explaining the SOFIX returns. The paper concluded that volatility shocks are continuous and historical share prices have an impact on the volatility of current shares.

Vasudevan and Vetrivel (2016), investigated the GARCH model and if it can be used to forecast the Indian stock market. The study was conducted using data from 1 July 1997 to 31 December 2015 and the models used were the asymmetric GARCH models and the symmetric GARCH (1, 1). The results revealed that the symmetric GARCH model performed better in predicting the conditional variance of the BSE-SENSEX index returns than the symmetric GARCH model when taking into account the existence of the leverage effect.

A study that analyzed the relationship between share return and volatility of China and the South African share market was conducted by Cheteni (2016). The study made use of daily data covering a period from January 1998 to October 2014. The GARCH model was used to evaluate the volatility of the Shanghai Share Exchange composite index and the FTSE/JSE

Albi index. The results show that there is high volatility in both the Shanghai Share Exchange and the JSE market. Furthermore, the examination uncovered that volatility was continuous in both countries and resembled similar movements in returns.

Dana (2016) examined the volatility of Jordan's capital market. This study analyzed a period starting from 1 January 2005 to 31 December 2014 of the Amman Share Exchange (ASE). The ARCH, GARCH, and EGARCH methodologies were applied. The empirical results indicated that the symmetric ARCH/GARCH models could forecast ASE volatility and provide more evidence for leptokurtic features. On the other hand, the E-GARCH results indicate that there is no evidence of the leverage effect on the Amman Stock Exchange.

The adequacy of the GARCH models in modeling the volatility of the JSE monthly returns for the period from January 1991 to February 2008 was investigated by Mtemeri (2009). The data used was randomly selected from various sectors of the South African economy. The results showed that GARCH (1, 1) is a good forecasting tool for the short term. Furthermore, it was discovered that the use of higher GARCH orders such as the GARCH (2, 1), GARCH (1, 2) or GARCH (2, 2) was inferior to the GARCH (1, 1).

The adequacy of the GARCH models in modeling share market indices for 13 emerging markets: 3 from Asia, 7 from Latin America and 3 from East Europe. Bonilla and Sepúlveda (2011), used the Engle's ARCH test and the Hinich portmanteau bicorrelation test. The results showed that the GARCH formulation provided an efficient characterization for the underlying process for all 13 emerging markets under this study. This study also investigated the presence of ARCH effects using the Engle's Lagrange Multiplier test and it was found that there was no evidence of ARCH effects on a long period of time. It was then concluded that policymakers should take caution when applying the autoregressive model for forecast and policy analysis because the inadequacy of the GARCH models has implications on the risk management, portfolio selection and pricing of share index options.

The GJR-GARCH (1, 1), EGARCH (1, 1) and GARCH (1, 1) models on the daily movement of five JSE indices was investigated by Niyitegeta and Tewar (2013). The study analyzed data for the period starting from 2002 to 2014, whilst also analyzing the effects of the 2007-2009 global financial crisis on the share volatility behavior. GJR-GARCH was found to be the best-fitted model for all the indices except for the JSE/FTSE Top 40 Index and the EGARCH was the best-fitted model for the JSE/FTSE Top 40 Index. These results applied before, after and during the financial crisis.

Jonsson (2016), tested the forecasting power of the candlestick pattern on the Swedish share market using bootstrapping and the GARCH-M analysis for the period of 9 years from 2007 to 2015. The results found that forecasting using candlestick patterns of technical analysis was not profitable in 29 OMXS30 shares in the short term.

The paper which used asymmetric and symmetric GARCH models such as EGARCH (1, 1), GRJ-GARCH (1, 1) and GARCH (1, 1) models to forecasts and to estimate volatility in Saudi Arabia share market was conducted by Mhmoud and Dawalbait (2015). The main goal of the study was to compare the performance of various GARCH models. This study was based on the student-test, normal and GED distribution assumptions. The study used daily closing price data for the period starting from January 2005 to December 2012. The Mean Absolute Errors (MAE), Root Mean Square Errors (RMSE), Theil Inequality Coefficient (TIC) and the Absolute Percentage Errors (MAPE) were computed. The findings revealed that when estimating the conditional variance equation, the asymmetric GARCH models with the presence of heavy-tailed error distribution were superior to the GARCH model. Moreover, it was discovered that the GRJ-GARCH (1,1) model has the finest out-of-sample forecast for the Saudi Arabian share market and that the conditional variance process was highly persistent, which means that there was leverage effect in returns for the Saudi share market.

To examine the best model between the ARCH and GARCH models Effendi (2015) analyzed this model based on data from JKSE and share index from developed countries (STI, FTSE, and Nasdaq). The empirical findings revealed that when estimating volatility the GARCH (1, 2), GARCH (2, 2), GARCH (1, 1) and GARCH (2, 1) were the best fit models to estimate JKSE, FTSE, NASDAQ, and STI respectively.

Goyal (2000) tested the ability of various GARCH models in forecasting volatility of share returns. The volatility forecasts acquired from a variety of variance specifications and mean in

GARCH models were compared to the actual volatility. The results showed there was a negative significant relationship between share returns and unexpected volatility. In this paper, it was also discovered that the ARMA model performed better than the GARCH-M model.

Khan and Abdullah (2018) analyzed the use of forecasting models on predicting share volatility. The ARIMA (p, d, q) models were tested and it was found that the ARIMA (1, 2, 1) was the best fit to capture the share price volatility. In this study, the GARCH (m, k) model was fitted and the results indicated that the GARCH (1, 1) was adequate for predicting share price volatility. The Schwarz Bayesian Criterion (BSC) and the Akaike Information Criterion (AIC) were used to compare the ARIMA (1, 2, 1) and the GARCH (1, 1) model. The values for the AIC and BIC for the GARCH model were smaller than the values of AIC and BIC from the ARIMA model, and then it was concluded in this paper that the GARCH model is better than the ARIMA model in forecasting volatility.

The GARCH models were examined using data based on the Johannesburg Securities Exchange (JSE). The research was based on a period of 12 years using daily log-returns of the JSE ALSH, Top 40, Industrial 20 and Resource 20. The univariate GARCH models used were GARCH (1,1), EGARCH (1,1), PGARCH (1, 1) and GJR-GARCH (1,1). Both the asymmetric and symmetric models were examined, and the results indicated that the GARCH (1, 1) model was better than other models when modeling volatility clustering and leptokurtosis of the JSE sectorial indices (Masinga, 2016).

The main goal of Goudarzi and Ramanarayanan’s (2010) paper was to analyze the volatility of the Indian stock market and its stylized facts using the ARCH and GARCH models. This study analyzed a period over 10 years and the data used was based on the BSE500 share index. The study selected the symmetric volatility models, the ARCH and GARCH models, using the AIC and SBIC selection criterion. The results found that GARCH (1, 1) model describes volatility in the Indian stock market and its related stylized facts including fat tails, volatility clustering, and mean-reverting satisfactorily.

3.4. Active versus Passive managers and EMH theory

In recent years financial managers and investors have increasingly questioned the effectiveness of active managers in timing the market (Malkiel, 2003). Chopra (2011) assessed the ability of mutual fund managers in selecting shares that has high returns. The methodology used in this study is the Merton-Henriksson and the Jensen’s alpha, this paper was based on 36 mutual funds in India for the period starting from January 2001 to September 2009. And it was found that on average the fund managers are not able to predict share prices well enough to outperform the buy and hold strategy.

To evaluate the performance of 18 equity unit trust funds, on the Zimbabwean Stock Exchange for the period 1999 to 2005. Chikore and Gachira (2011) used the Sharpe ratio, Treynor and Jensen’s measure inter alia methodologies. The results show that only one trust fund outperformed the market when the Sharpe ratio and Jensen’s measure was used, whilst, three funds outperformed the market when the Treynor measure was used, and the other 14 trust funds did not outperform the market. Therefore, this study concluded that on average the equity unit trust funds do not outperform the market.

A study to assess if technical analysts can direct investors to shares with returns that exceed the market’s return discovered that the analysis of past share prices or technical analysis cannot reliably predict future price movement. The study was based on the Singapore Stock Exchange from a sample of 292 technical analysis-based investment advice made over five years from November 1979 to April 1984 by the Singapore investment advisory company. The goal was to test whether the Singapore investment advisory firms were able to use technical analysis to select shares that would make investors earn excess returns. After adjusting for trading costs it found that the recommended shares did not beat the market and concluded that the Singapore market is “weak-form efficient” (Dawson, 1985).

To assess the performance of the United States' open-end equity mutual fund Kosowski, Timmermann, Wermers, and White (2006) used the bootstrap statistical tool. The results from the bootstrap tool show that the performance of mutual fund managers is not exclusively based on luck and that portfolio managers with genuine share-selection skills can generate profit to the mutual fund.

To test if financial experts can beat the market Wright (1994), used the first 20 months' results of the Wall Street Journal with their monthly announced share selections. The findings revealed that the monthly returns seem to show that active managers outperform the market after adjusting for risk. On the other hand, the assessment of daily returns indicated that all abnormal return happens in the in first two days of trading after the public announcement, and all the abnormal return is slowly removed by the market over the subsequent 39 trading days.

A paper that investigated the existence of the "weak form efficient" in Pakistan used daily share return of the Karachi stock exchange (KSE). The study analyzed a period of 15 years from July 1997 to April 2012 and used the Phillips Perron test, Kolmogorov-Smirnov (K-S) test, runs test and the Augmented Dickey-Fuller test to check the hypotheses. The results found that KSE is not normally distributed and price patterns exist therefore, technical analysts can benefit in the short run by forecasting future price movements. It was then concluded that there are arbitrage opportunities in the Karachi share Exchange and investors who know how to read the market can benefit from it in the short run. However, it was further discovered that in the long run KSE market is a weak-form efficient market (Nawaz, Sarfraz, Hussain and Altaf, 2013).

A similar study to the one done by Nawaz *et al.*, (2013) was conducted in 2010 to test the weak form of the efficient market hypothesis on the Asia-Pacific market. The study analyzed monthly observations from January 2004 to December 2009. Runs Test, Autocorrelation, Ljung-Box Q-statistic Test, Variance Ratio and the unit root test were used to test the hypothesis that the Asia-Pacific markets follow a random walk. Hamid, Suleman, Alishah, Akash, and Shahid (2017), discovered that the monthly returns in Asia-Pacific share markets are not normally distributed because they are leptokurtic and negatively skewed. Therefore, it was concluded that traders can reap profits through the arbitrage process across these markets since monthly prices do not follow the random walk Hamid *et al.*, (2017).

Nisar and Hanif (2012) investigated the weak form of the efficient market in South Asia four major share exchanges which are Pakistan, Sri Lanka, Bangladesh, and India. The paper used daily, weekly and monthly data for a period of 14 years starting from 1997 to 2011 and the runs test, variance ratio, unit root test, and serial correlation were used to test the hypothesis. The study found that the South Asian markets do not follow the random-walk and that the weak form of the efficient market does not apply in these markets.

A study which was conducted in Nigeria by Ajao and Osayuwu (2012), was aimed to test the weak form of the efficient market hypothesis. The data used was monthly values from the all-share index from 2001 to 2010. The runs test and the serial correlation technique was used tests for the volatility of share price movement. The results show that successive share price changes are independent and random in the Nigerian Capital Market, thus the Nigerian capital market follows the weak form of an efficient market hypothesis.

Urquhart, Batten, Lucey, Mcgroarty, and Peat (2015), conducted research to study the profitability of intraday technical analysis in the silver spot and the gold markets using three famous moving average rules. Data for the precious metal was collected from 01/01/2008 to 10/09/2014 and the results discovered that intraday technical trading rules are not profitable in the silver market but offer a significant profit in the gold market.

The practicality of the EHM in the European share market was investigated by Borges (2010). In this study, the weak form of the EMH was tested on the market index of Germany, Greece, Spain, France, Portugal and the United States. The joint variance and runs tests were performed using daily and weekly data from January 1993 to December 2007. The outcome of this research showed mixed results of the viability of the EMH. The results for Greece and Portugal show that the EMH did not seem to hold, because of first-order positive autocorrelation in the returns. Data from the United Kingdom and France indicated the presence of mean reversion in weekly data and therefore the EMH was rejected. The results from Spain and Germany did not reject the EMH.

3.5. Summary

Existing literature shows that researches on the use of candlesticks and GARCH in predicting share prices are underexplored in South Africa. Many results discovered from the studies which were conducted to test the profitability of candlesticks support that the use of candlesticks is profitable and that investors may benefit from using it when predictions of the market's movement. These studies in favor of the Japanese candlestick patterns include Do Prado *et al.,* (2013), Lu *et al.,* (2013), Ameen (2013), Caginalp *et al.,* (1998), Jasemi (2011), Shiu and Lu(2011), Divanange *et al.,* (2013) and Goswami et al., (2009). In contrast, studies that found little use of the candlestick patterns include studies done by Tharavanij *et al.,* (2017), Young *et al.,* (2005), Young *et al.,* (2005) and Marshal *et al.,* (2008).

The findings from previous studies examining if technical analysts can outperform the market shows mixed results. Nawaz *et al.,* (2013), Nisar and Hanif (2012) and Wright (1994), suggest that in the short run the markets are not distributed normally and do not follow the random walk. These papers concluded that an active investment strategy can outperform a passive investment strategy which means that investors and traders are able to forecast share prices in the short run and reap profit through the arbitrage process. However, in Chopra *et al* (2011), Chikore and Gachire (2011) and Dawson (1085), Ajao and Asayuwu (2012), it was found that the markets follow the weak form of the efficient market and it was then concluded that active managers are unable to predict the market. Therefore from analyzing existing literature, it shows that there are no confirmed laws in finance about how the market works. Therefore, financial theories are thought to be subjective. Instead, ideas attempt to describe how the market works and there is no technique to quantify the market efficient and so testing the EHM is difficult.

CHAPTER 4

DATA AND METHODOLOGY

4.1 Introduction

This chapter outlines and explains the analytical approach used in the study to address the main objective. The chapter starts off by providing a discussion of the research paradigm, followed by the research design. The research design covers the candlestick patterns, the model specification, theoretical framework, definition of variables, econometric techniques and data sources.

4.2 Research Paradigm

A research paradigm is an approach to conducting research that has been approved by the research community or that has been in practice for many years (Kivunja and Kuyini, 2017). This research is located in an explanatory paradigm. It is an explanatory paradigm because it is a quantitative study and it involves testing theories from existing concepts (Kivunja and Kuyini, 2017). This paradigm is relevant for this topic because the research investigates the potential benefits of market timing from an active investment strategy, by testing if technical analysts can effectively make predictions about the market movements from using historical share prices. This paper also tests if the signals from the candlestick patterns can generate higher returns for investors. To answer these subjects this research employs mathematical and econometrics techniques as a means to test the existing theories.

4.3 Research Design

4.3.1 The Research Process

The first step in the empirical section was to identify the companies to be included in the study. Following that, the share price data for the sample period (stated below) were gathered in order to identify and plot the candlestick patterns. The final step was to apply the econometric techniques needed to test the potential profitability from market timing decisions based on the candlestick patterns.

4.3.1 Data Source

The main sources of data are Thomson DataStream (2019) and the IRESS SA (2019), previously known as McGregor BFA. The study examines daily data of ten companies for a period of ten years starting from 02 January 2009 to 31 December 2018. The reason for the choice of daily data is because sizable changes in the equity market may occur on a daily basis, allowing the study to track the development of trends. Lastly, daily data provides enough observations for econometric estimation as suggested by prior studies such as Fleming and Ostdiek (2001). This research is based on ten companies from the JSE Top 40 Index according to its 2019 composition. And daily share price data of these companies were sourced from Thomson DataStream (2019) and the IRESS SA (2019).

4.3.2 Definition of variables

The history of share prices was used to estimate future price movements. The sample of the ten companies from the JSE Top 40 Index was stratified based on sector and market capitalization. The JSE is the oldest existing and largest stock exchange in Africa (Johannesburg Stock Exchange, 2019). The JSE is also currently ranked as the 19th largest stock exchange in the world by market capitalization and the largest exchange on the African continent. The study used a sample from the above index. The sample covers the pharmaceutical, food, health, mining, telecommunication, entertainment, and finance industries. Brief descriptions are given below of the current share price trends of these companies and some observations by market analysts and commentators from generally available internet sources mainly as orientation for the more substantive analysis presented after that.

- Aspen Pharmacy Holding (APN) is listed on the JSE Top 40 and its shares are available for sale on the JSE. APN serves patients on a global scale through its nutritional and pharmaceutical products. APN has been the biggest generic medicine distributor in South Africa and its share price rose steeply from R100 in 2011 to more than R300 in 2016. This trend has made Aspen shares attractive to potential investors (Johannesburg Stock Exchange, 2019).

- Capitec Bank Holding LTD (CPI) was established in 2001 and has become the fastest-growing bank in South Africa. CPI commands over 20 percent of the banking market share in South Africa, with a market capitalization close to R70 billion. CPI reported that in the 2016 financial year its share price increased by 16 percent p.a., while its investors enjoyed a 26 percent increase in the dividend (Johannesburg Stock Exchange, 2019).
- Discovery LTD (DSY) offers a range of products in insurance, medical aid, investment and credit cards. Its shares are listed for sale on the JSE. Performance highlights for the company show that in 2016 earnings rose by 16 percent p.a. with a market capitalization of R76 billion. However, recent online stock charts show a decline in stock prices for Discovery. Nonetheless, the company mentioned that its new business investment is expected to increase the company's profits as well as dividends (Johannesburg Stock Exchange, 2019).
- Kumba Iron Ore LTD (KIO) is a mining company in South Africa. It is a subsidiary of Anglo American. KIO is the fourth-largest supplier of iron ore in the world and the biggest in Africa. KIO shares are available for sale on the JSE with a market capitalization of R44.5 billion. KIO's overall performance has declined recently due to difficult conditions in the local mining industry and the global steel industry. The online stock charts indicate that the KIO stock price has dropped from a high of over R600 in 2013 to R137.50 by August 2016 (Johannesburg Stock Exchange, 2019). This indicates that the short to the medium-term outlook of the share price does not seem favorable, particularly should iron ore prices continue to fall. However, the company has indicated that it has faith in its restructuring process that has equipped it for the difficult conditions and that continuing attention will focus on reducing costs in the future.
- Mondi PLC (MNP) is the largest international paper and packaging group. Its shares are listed on the JSE and on the London Stock Exchange. In 2015 the company recorded a 25 percent increase in operational profit. The online stock chart shows a decrease in the MNP share price and this is explained by the weakening of the Rand and the slow economic growth in South Africa. However, the losses have been decreasing. Mondi PLC is now focusing on creating a firmer "Mondi share price" through developing "green" products which would create new market exposure and add more diversification (Johannesburg Stock Exchange, 2019).

- Mr. Price Group LTD (MRP) is one of the largest retail companies in South Africa. Mr. Price's shares have been listed on the JSE since 1952 and its shares have been available on the JSE since then. In June 2016 Mr. Price reported sales totaling more than R20 billion. The company has reported that because of the slow economic growth in South Africa, the customer environment is expected to stay depressed for a short-term period as the nation carries on with recovering. However, the company is diversifying into Africa and has also started opening stores in Australia. The live online stocks chart indicates that the MRP share price has been falling, but it is recovering slowly (Johannesburg Stock Exchange, 2019). This provides investors with an opportunity to buy shares at low prices, which is expected to perform better over the long term.
- MTN Group LTD (MTN) has more than 300 million subscribers. The company's shares are available on the JSE. In the past five years, its dividend increased by more than 273 percent. Nevertheless, the online stock chart indicates that its share price has been fighting to recover after the massive $3.9 billion fine it incurred in 2015 in Nigeria (Johannesburg Stock Exchange, 2019). After the fine, its growth slowed down compared to in the past years. However, MTN has established its company in the global market and its shares should make profits in the future.
- Naspers LTD (NPN) is a media, entertainment and internet company, operating in more than 130 countries. NPN shares are available on the JSE. The latest financial report shows good progress across the internet platform and the Naspers video-entertainment. This has made Naspers' share price to rise faster than its competitors. In 2015 Naspers' earnings increased by 30 percent. Its share price has been outperforming the all-share index of the JSE by almost 300 percent (Johannesburg Stock Exchange, 2019). The live online stock chart indicates a sizable rise in the NPN share price recently and this upswing is expected to persist as the company makes more investments and international acquisitions.
- SASOL LTD (SOL) is an international energy and chemical company that operates in 36 countries. Its shares have been listed on the JSE since 1979 and were also listed on the New York Stock Exchange in 2003. SASOL has a market capitalization of R311 billion which makes it one of the biggest companies listed on the JSE. The group has been partnering with international projects. In 2014 the company had its highest share price of R652.99, which was followed by a sharp decrease of around R400 in just a few months. After that, the company has been battling with rising costs of production, which

has forced it to close some operations and to cut thousands of jobs. The SASOL share price growth has been slow in the previous few years.

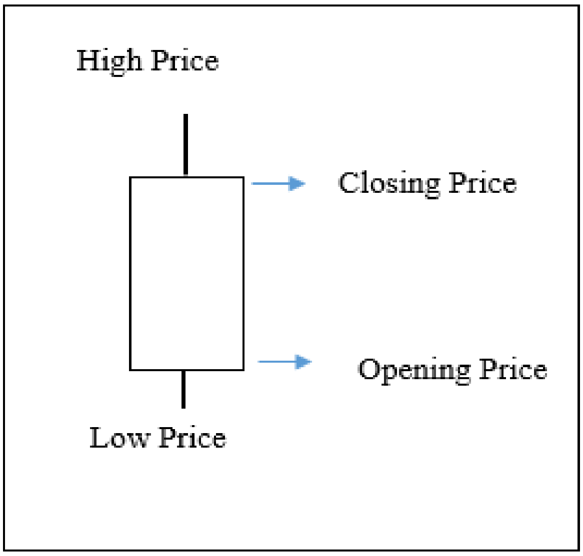
- Shoprite Holdings LTD (SHP) is an investment holding company which together with its subsidiaries constitutes the biggest and fastest-growing retail operation in Africa. Shoprite's shares are listed on the Zambian, Namibian and the Johannesburg stock exchange. Shoprite continues to grow by opening new stores to meet the needs of the growing population (Johannesburg Stock Exchange, 2019). In addition, the live online stock chats indicate that the company's share price has shown a steady increase which means that investors who buy their shares may acquire good long term returns on the investment.

4.3.3 Theoretical Candlestick Patterns

A "candlestick" is a well-known procedure of technical analysis (Kamo and Dagli, 2009). It originated from the Japanese rice merchants and traders who tracked the market prices and daily momentum hundreds of years before becoming popularized in the United States of America and other countries (Kamo and Dagli, 2009). Each observation on candlesticks displays four main points. These are the high, low, opening and closing prices (Marshall *et al,* 2006). The candlestick has a "wide part" which is called the "real body" which shows the range between the opening and closing price. This indicates whether the closing price was higher or lower than the opening price. Candlestick charts can be composed of daily, weekly or longer data. The color of the real body indicates whether the closing price was lower or higher than the opening price. It can be plotted in black and white or the chartist can choose to use red and green. A green candlestick is the same as the white candlestick and it shows that the opening price was lower than the closing price. A red or black candlestick indicates that the opening price was higher than the closing price (Marshall *et al,* 2006).

4.3.3.1. A White Candlestick

A typical white candlestick is shown in Figure 4.1.



Source: Edwards *et al.* (2018)

Figure 4.1. White Candlestick

A white candlestick as in Figure 4.1 normally indicates a bullish market. This candlestick has a closing price that is higher than the opening price (Marshall *et al.*, 2006). What takes place after the opening price is shown by the "shadow" or the "wicks", and these are represented by black lines. The wicks show the price movements after the opening price. The lowest point on the wick shows the lowest price of a security which occurred in that period and the highest point of the wick shows the maximum price that occurred in that period. Following the open, low and high price is the closing price, which indicates the last security price for that period.

4.3.3.2. A Black Candlestick

The normal shape of a black candlestick is portrayed in Figure 4.2.

Source: Edwards *et al.* (2018)

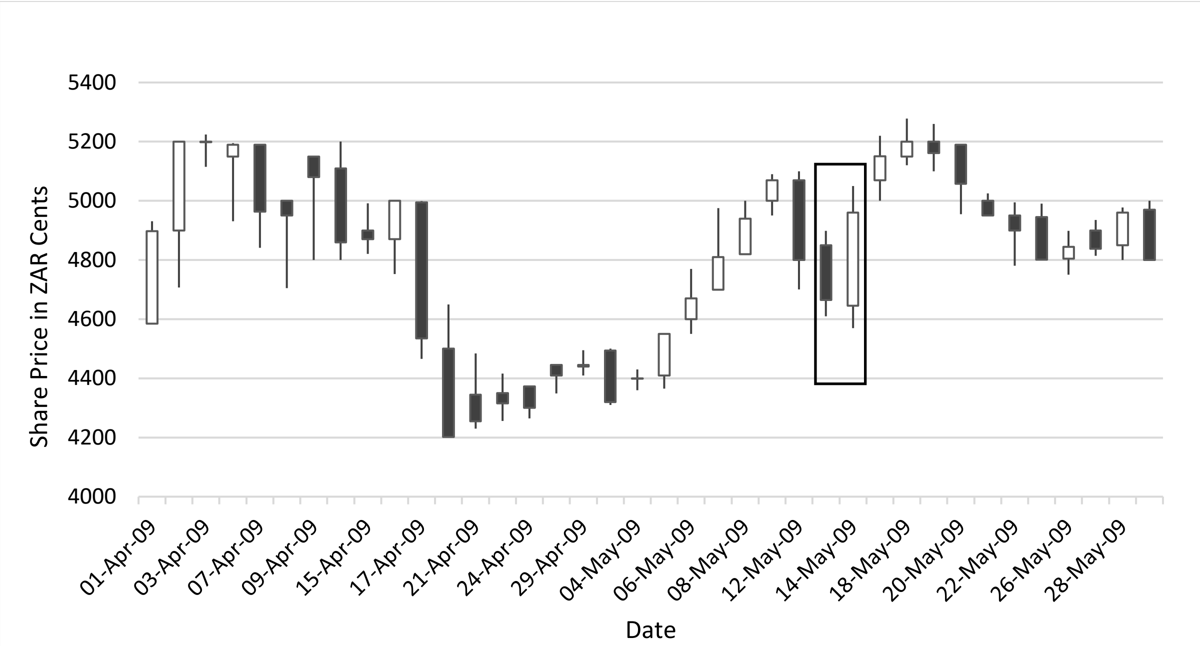
Figure 4.2. Black Candlestick

As shown in Figure 4.2. a black candlestick is very similar to a white candlestick. The only difference between the black and the white candlestick is that on the black candlestick the closing price is below the opening price. Since the closing price is below the opening price, this candlestick typically represents a down or bearish trend in the market.

4.3.3.3. Candlestick Reversal Patterns

Up and down movements in share prices would typically manifest in candlestick reversal patterns. These are often used by market analysts to predict future trends, by paying attention to distinguishable characteristics. Candlestick patterns show the movements of security prices in the form of charts. These patterns are made from a combination of two or three individual single lines (Marshall *et al*, 2006). There are several different types of patterns, and most have slight differences to others on the same basic principles. The following paragraphs will discuss the candlestick patterns used in this study, in particular, the ones which represent the bullish doji, hammer, bullish engulfing, piercing lines, shooting star, hanging man, bearish engulfing and the dark cloud cover. These patterns were selected because they are very common and are considered major reversal patterns. Another reason for including them was because there are not many mathematical definitions of the candlestick patterns in the existing literature. They can, therefore, be used scientifically by specifying formulas/functions in Excel (Ameen 2013).

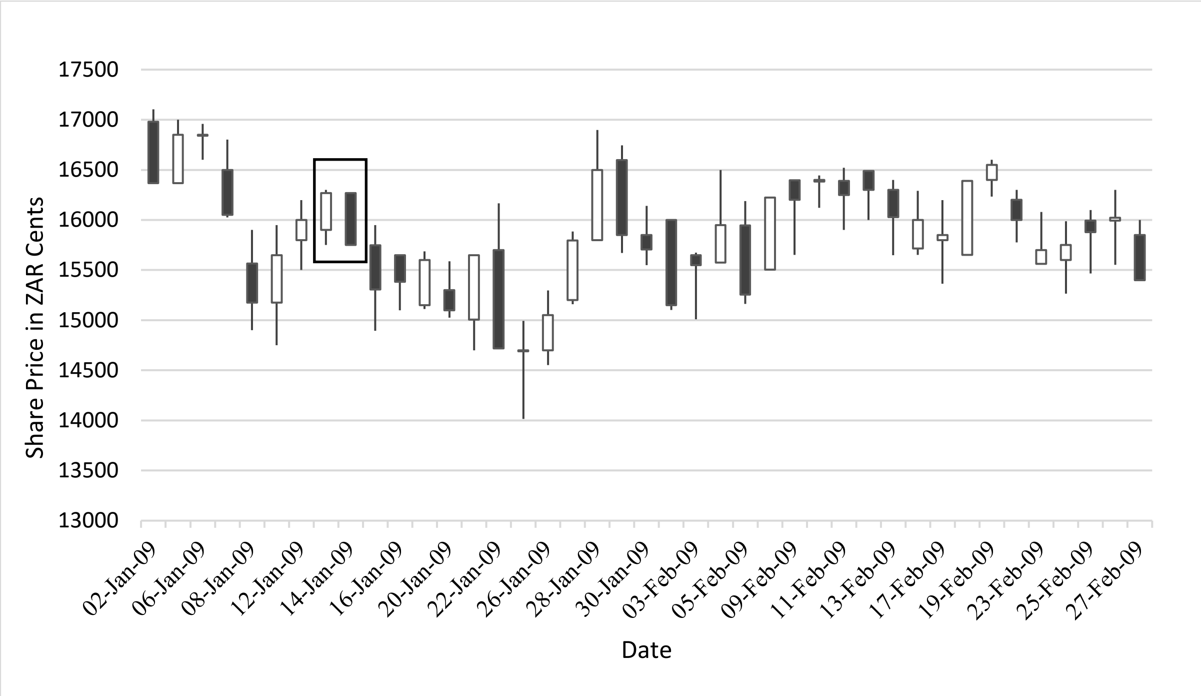
What follows now, are some examples of candlestick patterns drawn from the share price data of the companies selected for the study. These graphs are for purposes of illustration and cover only two months of the ten year sample period. For example, Figure 4.3 illustrates the bullish engulfing pattern that was particularly evident in APN's data. However, the findings from the figures are not discussed in detail here but will be reported in Chapter 5.



Source: IRESS SA (2019)

Figure 4.3: Bullish Engulfing Pattern, APN, April 2009 – May 2009

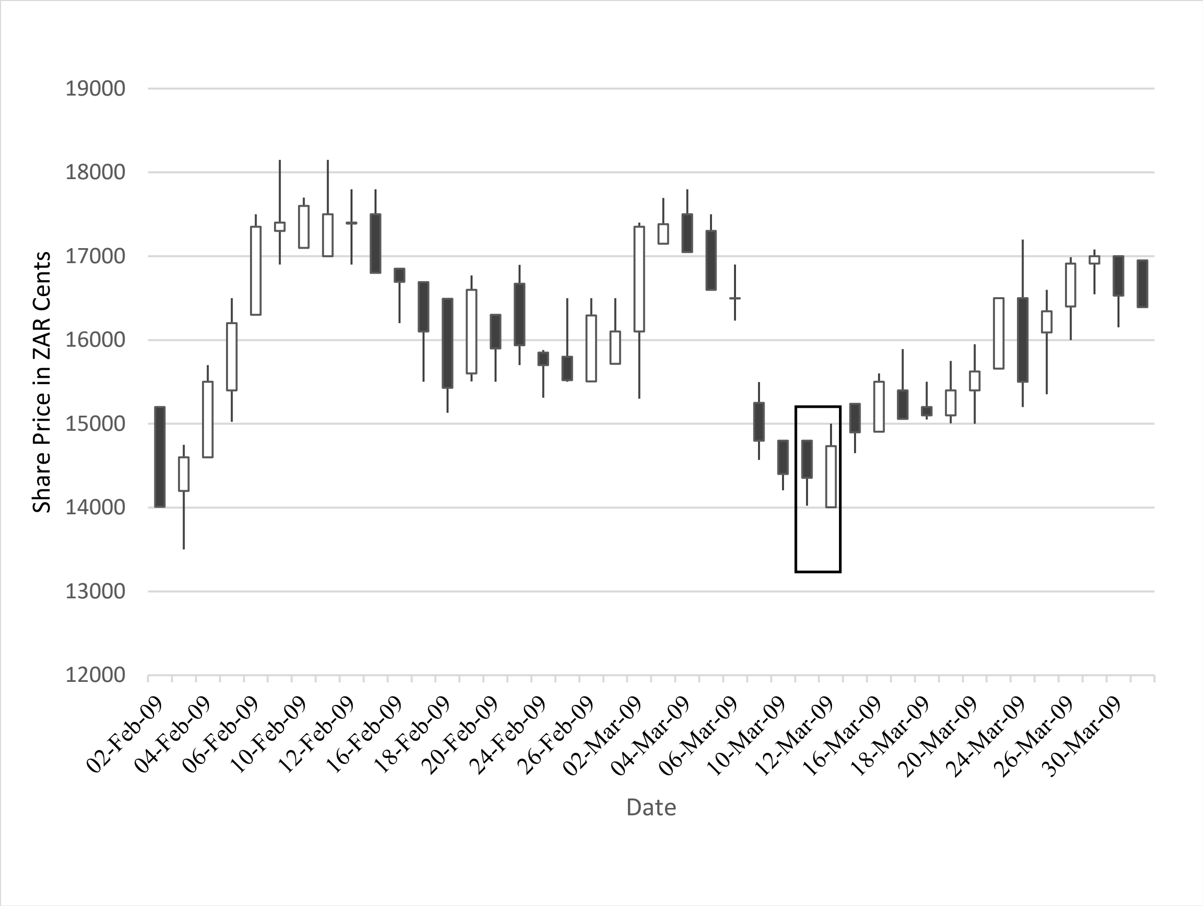
Figure 4.3 above shows a visual representation of the bullish engulfing patterns. This graph was created using the returns of APN. The bullish engulfing pattern is a two-candle reversal pattern that appears at the turning point of the downtrend. In this pattern, the first candlestick is a bearish candle which is shown by a small body and the second candlestick is characterized by a bullish body. Figure 4.3 shows a rectangular box, which highlights the bullish engulfing pattern. It also shows that the second candle opens at a price lower than the price of the first candle and it closes at a price higher than the price of the first candle (Edwards *et al.*, 2018)



Source: IRESS SA (2019)

Figure 4.4: Bearish Engulfing Pattern, Naspers LTD, January 2009 to February 2009

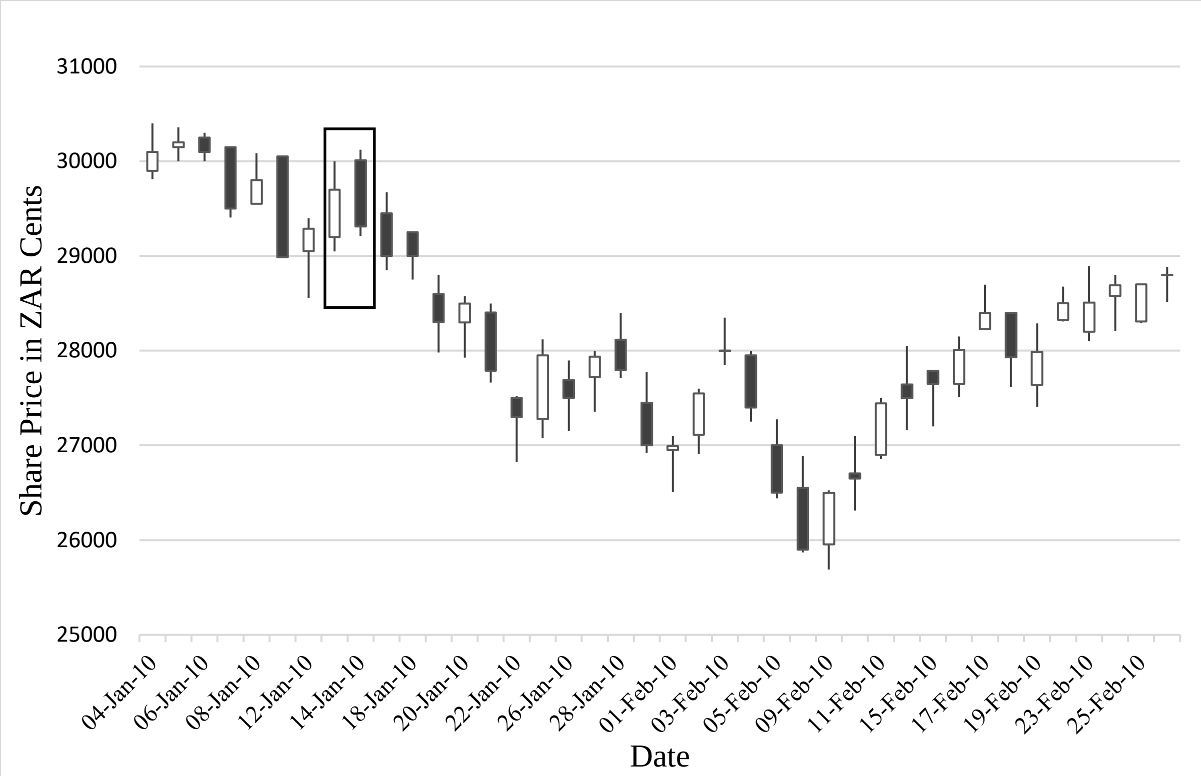
Figure 4.4 above depicts an example of the bearish engulfing pattern from Naspers LTD data. This configuration is a two-candle reversal pattern that usually appears at the turning point of the uptrend. In this pattern, the first candle is a bullish candle, as shown by a white body and the second candlestick is characterized by a bearish candle (Edwards *et al.*, 2018). The small rectangular box in Figure 4.4 highlights the bearish engulfing pattern which shows that the second candle opened at a price which was higher than the price of the first candle and it closed at a price lower than the price of the first candle.



Source: IRESS SA (2019)

Figure 4.5: Piercing Line Pattern, Kumba Iron Ore LTD, February 2009 to March 2009

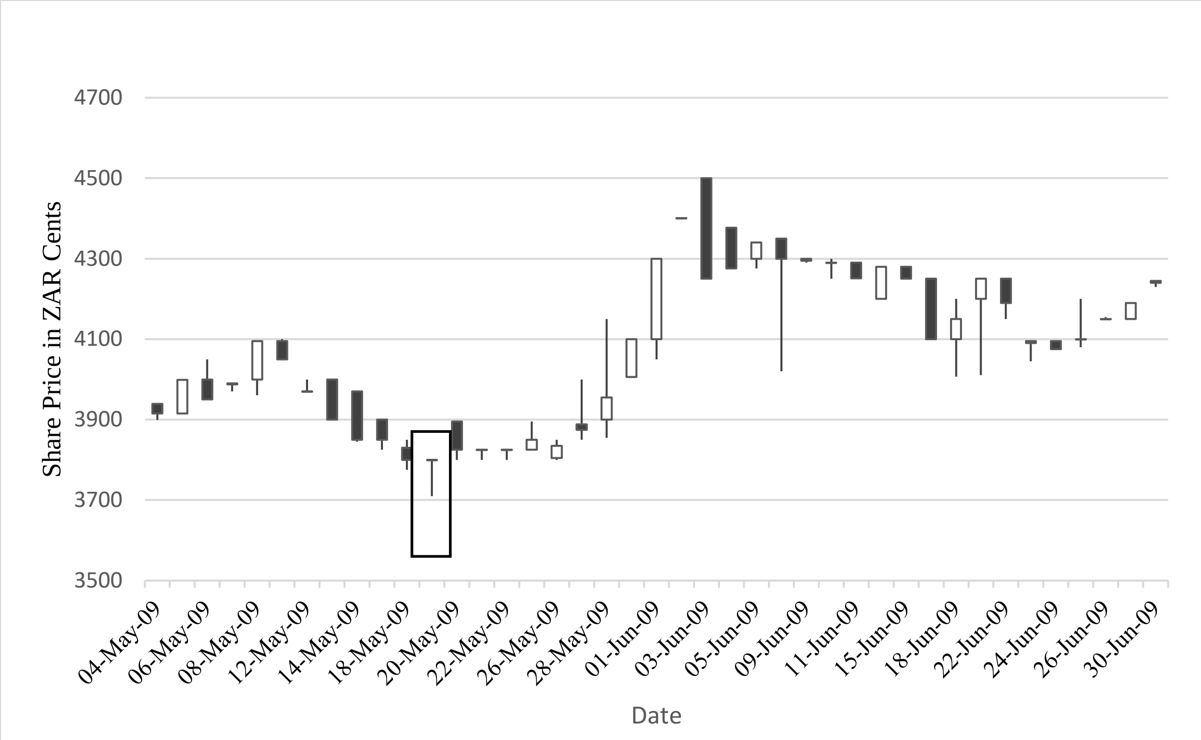
Figure 4.5 depicts the piercing line example. This chart was plotted using data from the Kumba Iron Ore LTD company. The piercing line is a bullish reversal candlestick pattern. It forms during the rising of an uptrend or at the bottom of a downtrend. This pattern has two components, the bearish and the bullish candle. The first candlestick is a bearish candlestick and the second candlestick is bullish. The second candlestick opens below the low price of the first candlestick and closes above the midpoint of the first candlestick (Edwards et al., 2018).



Source: IRESS SA (2019)

Figure 4.6: Dark Cloud Cover Pattern, Naspers LTD, January 2010 to February 2010

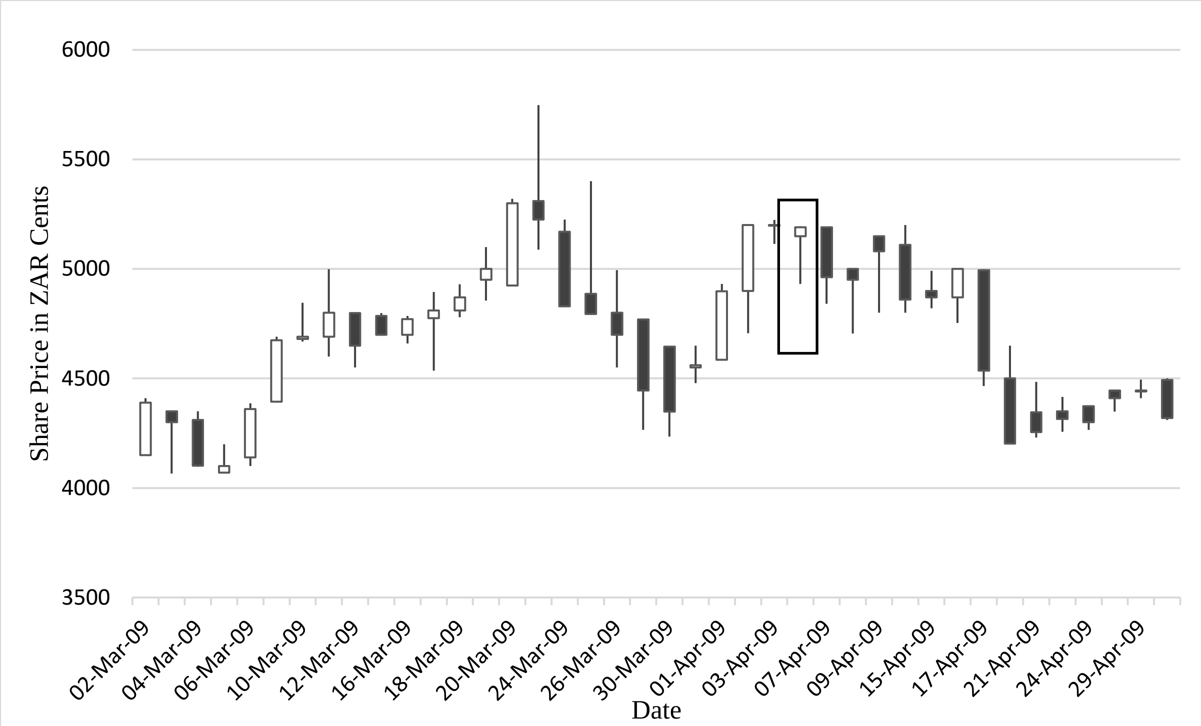
Figure 4.6 above is the dark cloud cover pattern. This chart was drawn using data from Naspers LTD. The dark cloud cover is a bearish reversal pattern that appears in an uptrend and it signals a potential decrease in the asset's prices. This pattern is a two candlestick pattern, the first candle is white with a long real body which is followed by a candle which starts at a new high price. It then closes at a price that is below the center of the first day (Ameen 2013). This pattern is more reliable when the second candlestick close at the price below the middle of the first candle (Edwards et al., 2018).



Source: IRESS SA (2019)

Figure 4.7: Hammer Pattern, Capitec Bank Holding LTD, May 2009 to June 2009

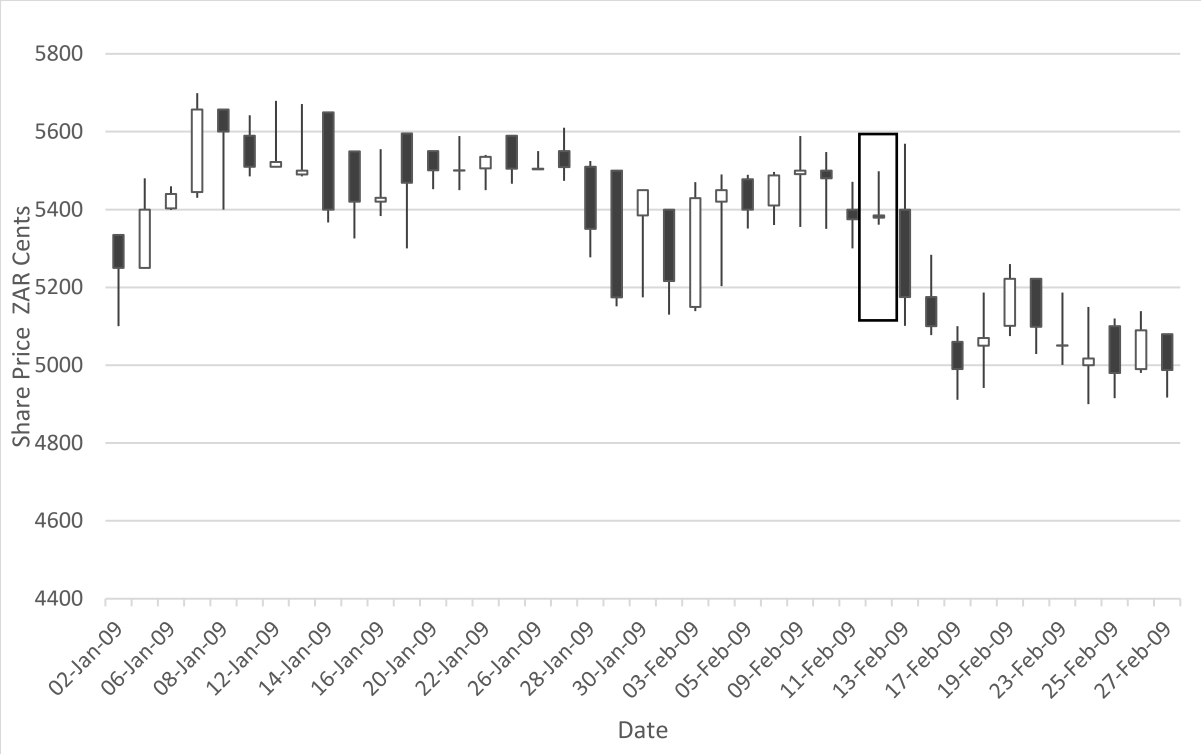
Figure 4.7 above is an example of the hammer candlestick pattern. This was drawn using data from Capitec Bank Holding LTD. This pattern usually occurs at the lowest point of a downward trend and is seen as a bullish reversal. It is characterized by a small body whereby the low, high, open and close are almost the same. The lower shadow under the body is more than twice the length of the candlestick body (Edwards *et al.,* 2018). In this pattern the bullish body is more favorable, however, the body may sometimes be bearish.



Source: IRESS SA (2019)

Figure 4.8: Hanging Man Pattern, Aspen Pharmacy Holding, March 2009 to April 2009

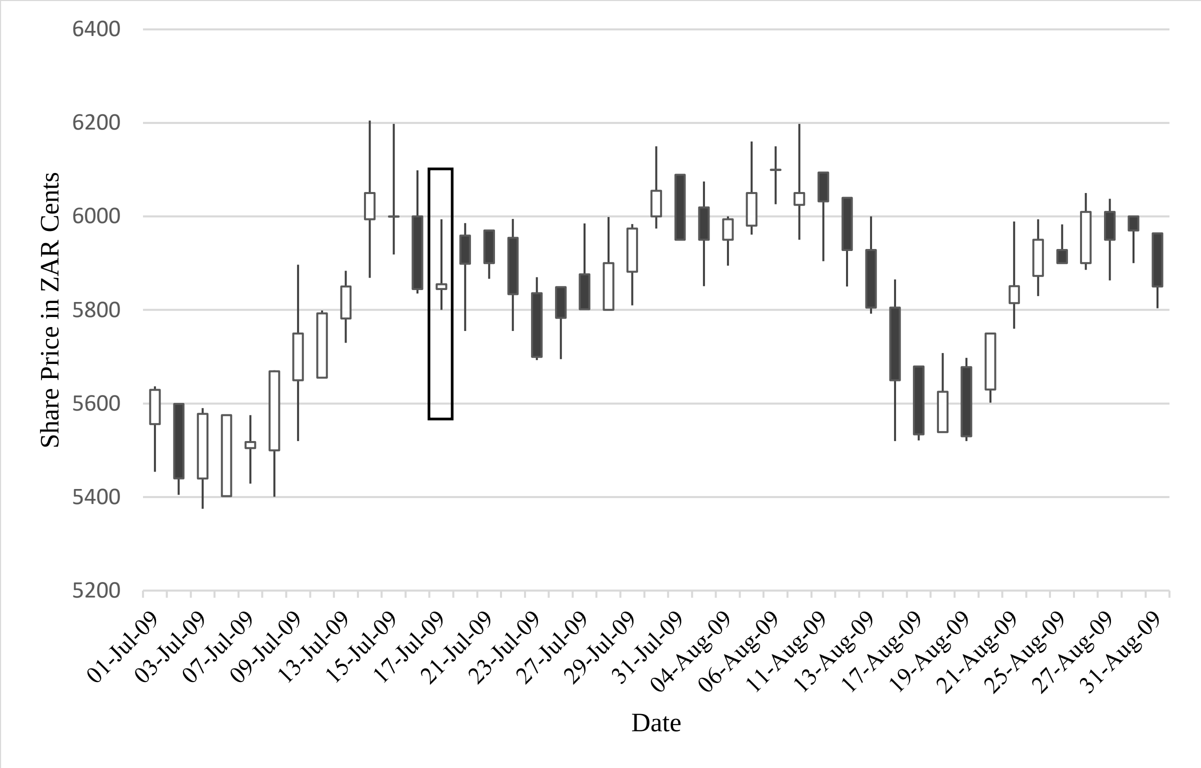
Figure 4.8 above shows an example of the hanging man pattern. This graph was plotted using data from APN. The hanging man is a bearish reversal pattern that is represented by one candle. This pattern mainly occurs at the turning point of an uptrend. It signals a drop in security prices (Edwards *et al.*, 2018). The small rectangular box highlights the hanging man pattern. This candlestick pattern has a long lower wick which is more than twice the length of the real body (Edwards *et al.*, 2018).



Source: IRESS SA (2019)

Figure 4.9: Shooting Star, Shoprite Holdings LTD, January 2009 to February 2009

Figure 4.9 shows an example of the shooting star pattern, which was drawn using data from Shoprite Holdings LTD. The shooting star is a bearish reversal pattern that is a single day pattern. The shooting star has an upper wick which is long and is about twice the size of the real body.



Source: IRESS SA (2019)

Figure 4.10: Bullish Doji, APN, July 2009 to August 2009

Figure 4.10 above depicts a bullish doji pattern using APN data. This pattern occurs when the opening and the closing prices are virtually equivalent. The length of the lower and the upper wicks can differ, and the resulting candlestick shape looks like a plus sign or an inverted cross. Doji suggests a sense of indecision between the buyers and the sellers. Prices typically move below and above the open price level during the session, but the closing price is near the opening price.

4.3.5 Econometrics Techniques

As indicated in Chapter 2, the empirical analysis of the candlestick patterns needs to be augmented by Econometric techniques. The ones used in this study are now discussed.

4.3.5.1 ARCH Model

Modeling and predicting stock market volatility has been the theme of sizable theoretical and empirical investigation over the past decades. The drive for this line of inquiry is that in finance volatility is an important concept (Abdullah and Khan, 2018). Volatility is measured by the variance of return or by the standard deviation and it is often used to measure the risk of financial assets (Abdullah and Khan, 2018).

The popular non-linear models in finance are the GARCH and the ARCH models which are used for modeling and to make predictions about future volatility. The ARCH stands for 'autoregressive conditionally heteroscedastic' (Brooks, 2002:426). One of its fundamentals is that it deals with the non-stationarity (time-variant mean) and stationarity (time-invariant mean). The important feature of the ARCH is known as 'volatility pooling' or 'volatility clustering' which explains the tendency of huge changes in asset prices. Before estimating the GARCH model the first step is to test that the class model is suitable for data by computing the Engle (1982) test for ARCH effects (Brooks 2002:426). When computing the ARCH test, high-frequency data such as quarterly, monthly, weekly or daily data should ideally be used. The existence of ARCH is tested by regressing the squared residuals on p-lag where p is a constant and is set by the user. Equation 3 below shows the ARCH (1) model.

$y_t = \beta_1 + \beta_{2x2t} + \beta_{3x3t} + \beta_{4x4t} + u_t$

$u_t = v_t\sigma_t \; v_t \quad \sim N(0, 1)$

$\sigma_t^2 = \alpha_0 + \alpha_1 u^2_{t-1}$ ....(4.1)

Equation 4.1 above could be broadened to include the general case where there are q-lags of the squared errors and this model is known as the ARCH (q) written below as equation 4.2.

$\sigma_t^2 = \alpha_0 + \alpha_1 u^2_{t-1} + \alpha_2 u^2_{t-2} + \cdots + \alpha_q u^2_{t-q}$ ....(4.2)

v_t is normally distributed with unit variance and zero mean. u_t is also normally distributed with variance σ_t^2 and zero mean.

4.3.5.2 GARCH Model

GARCH stands for generalized autoregressive conditional heteroscedasticity. This model was established by Taylor (1986) and Bollerslev (1986). The GARCH model is distinguished from other models such as the least square model which assumes that the relationship between the dependent and independent variable is homoscedastic (constant random disturbance) (Brooks, 2002). This model comes in and uncovers the volatility measures which can be used to predict residuals. This model allows the conditional variance to depend on its previous lags. In its simplest form GARCH (1, 1) is modeled as:

$$h_t = \gamma_0 + \delta_1 h_{t-1} + \gamma_1 u^2_{t-1} \quad \text{……..……………………………………………………………}(4.3)$$

The general form of the GARCH model is expressed as GARCH (p, q), which is written below as equation 4.4.

$$h_t = \gamma_0 + \delta_1 h_{t-1} + \ldots + \delta_p h_{t-p} + \gamma_1 u^2_{t-1} + \ldots + \gamma_q u^2_{t-q} \text{…………………………………………}(4.4)$$

h_t is the conditional variance, γ_0 is a constant p is the number of residuals and q is the degrees of freedom.

4.3.6 Mathematical Techniques

4.3.6.1 Excel Patterns Formulas

To identify the candlestick patterns the Excel functions “IF” and “AND” were used, as in the study by Ameen (2013). Equation 7 to 14 denotes five columns on Excel: Column A, B, C, D, and E is the Date, Open, High, Low and Close values of the share prices respectively. The formulas start from raw 4 which represents today’s value, raw 3 is yesterday’s value, raw 2 is the day before yesterday’s value and raw 5 represent tomorrow’s value.

BullishEngulfing=IF(AND((B3>E3);(E4>B4);(E4>B3);(E3>B4);((E4-B4)>(B4-E3));(C4>C3);(D4<D3));"1";"0")……………………………………...……………..…(4.5)

BearishEngulfing=IF(AND((E3>B3);(B4>E4);((B4-E4)>(E3-B3));(E3<B4);(B3>E4));"1";"0")…………………………………………….……………(4.6)

Piercing-Lines=IF(AND((E3<B3) ;(((E3+B3)/2)<=E4);(B4<E4);(B4<E4);(E4<B3);
(B4<D3) ;((E4-B4)/(0,001+(C4-D4))>0,6));"1";"0")…………………..…………………(4.7)

DarkCloudCover=IF(AND(E3>B3;B4>C3;B4>E4;B3<B4;E3>E4;E3<B4;B3<E4;E4<=(0,5*(C3+D3)));"1";"0")……………………………………………………….…………..……(4.8)

Hammer=IF(AND((C3-D3)>(3*(B3-E3));((E3-D3)/(0,001+C3-D3)>0,6);((B3-D3)/(0,001+C3-D3)>0,6);(E5>E4));"1";"0")…………………….………………………..(4.9)

HangingMan=IF(AND((C3-D3)>=(2*(ABS(B3-E3)));((E3-D3)/(0,001+C3-D3)>=0,75);((B3-D3)/(0,001+C3-D3)>=0,075);(E4<E3));"1";"0")……………….…………………………………..…..…(4.10)

ShootingStar=IF(AND(B3<D3+(0,5*(C3-D3));E3<(D3+0,5*(C3-D3));OR(B3<D3+0,9*(C3-D3);E3<D3+0,9*(C3-D3));(E4<E3));"1";"0")…………………...……...……..……(4.11)

BullishDoji =IF(B3=E3;"1";"0") ………………………………………………………(4.12)

4.3.6.2 Return Calculation

A similar assumption than the one used in Tharavanij and Siraprapasiri (2017) is applicable here. This is that investors buy shares at its opening price on the day after a bullish pattern is identified. The share is typically held over a 4-day holding period and then sold at the closing price. The holding period continuous return is calculated in the following manner:
$r^{c}_{t+h}=\ln C_{t+h}-\ln o_{t}$………..……………………………………………………….………(4.13)

The superscript “c” is the continuous return and “h” is the holding period. The variables “c” and “o” are the closing and opening prices respectively. This research calculated the average return of various shares with the same holding four-day holding period. The average returns then used to determine the profitability of candlesticks. The bullish candlestick patterns are “valid” or can give the correct signals about the market movement when the mean returns are positively significant and the bearish candlestick patterns are valid when the mean returns are negatively significant.

4.3.6.3 Binomial Test

The probability of the right predictions is defined as the total number of correct predictions divided by the total number of observed predictions or signals (Tharavanij and Siraprapasiri, 2017). A binomial test is used to check the predictive power of candlestick patterns. The probability of correct signals should be more than 0.5 if candlestick patterns can predict the security price movement in the short term (Tharavanij and Siraprapasiri, 2017). The binomial equation may be expressed as equation 4.14 below:

Binomial Test = nC / N…………………………………………..………………..…(4.14)

4.3 Summary

This chapter described and detailed data and methodology that were used to get the results which are presented in the following chapter. The methods and procedures that were chosen for this study were deemed to be the most appropriate after reviewing the existing empirical evidence discussed in the previous chapter (Chapter 3).

CHAPTER 5

RESULTS AND DISCUSSION

5.1 Introduction

This research aims to test the correlation between past share prices and future share prices and to analyze the earning potential of the South Africa equity market using the Japanese candlestick methodology as a market timing technique. In pursuit of these objectives, section 5.2 will test if historical share prices can explain future share price movement using the ARCH and GARCH models, section 5.3 will analyze the potential benefits of market timing as part of an active portfolio management strategy by calculating the mean returns that would be generated from the candlestick patterns signals and section 5.4 presents the results of the binomial test which shows the probability of the candlestick patterns when giving correct signals.

5.2 GARCH Models

This section makes use of the GARCH model to test the usefulness of employing historical price data when making predictions about the share price movements. The data used to run the GARCH model on Eviews is stationary data. Appendix A shows the dickey fuller unit root test results for all the companies analyzed under this study. The results show that in level terms data is non-stationary however in the first difference it is stationary. Appendix B also shows the stationarity of data using graphical representation and the results are similar to those from the dickey fuller unit root test where data is stationary in the first difference. Before estimating the GARCH models the first step was to test for the ARCH effects and the results are presented under Appendix C. The ARCH test explains the tendency of huge changes in asset prices (Abdullah and Khan, 2018). When the ARCH effects are present it means that the GARCH is appropriate for the data sample and when there are no ARCH effects it indicates that the GARCH model is not the best model for the data sample. Appendix C shows that the differenced APN, CPI, DSY, KIO, MNP, NPN, SHP and SOL have an ARCH effect and MTN company has no ARCH effect. However, since the objective here is to demonstrate and to estimated GARCH models the MTN ARIMA models will be transformed into a GARCH model. Tables 5.1 to 5.10 below show the results of GARCH (1, 1) models with mean equation and the variance equation.

The variance equation has three coefficients, the C is the intercept, RESID (-1) ^2 (ARCH (1)) is the squared return in first lag and GARCH (-1) is the conditional variance in first lag. The results for all the companies under this study have a sum of the ARCH and GARCH coefficients which is less than one and this indicates that there is a mean-reverting variance process (Brooks 2002). The mean-reverting process shows that a security's price will move to the average price over time and in this paper, the mean reversion is close to the value one this indicates that this process reverts slowly.

Table 5.1: GARCH model for Aspen Pharmacy Holding

Mean Equation				
Variables	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000765	0.000310	2.470900	0.0135
AR (1)	0.555561	0.215071	2.736588	0.0062
MA (1)	-0.615032	0.210724	-2.918657	0.0035
Variance Equation				
C	1.15E-05	1.84E-06	6.230349	0.0000
RESID (-1)^2	0.080747	0.007142	11.30553	0.0000
GARCH (-1)	0.887649	0.010545	84.17854	0.0000
R-Squared	-0.000313	Akaike info criterion		-5.248449
Durbin-Watson stat	1.907497	Schwartz Criterion		-5.234453

Source: Eview output using Thomson Reuter Datastream (2019).

The upper part of table 5.1 above is the ARIMA (1, 1, 1) results, with the probability of the AR(1) and MA(1) approximately zero, this shows that the ARIMA (1, 1, 1) model is good for forecasting the mean share price for APN but when volatility is not taken into consideration. The bottom part of table 5.1 is the variance equation results which can be written as:

σ^2 =1.15E-05 -0.080747u^2_{t-1} + 0.887649 σ^2_{t-1}.. (5.1)

The probability of the ARCH term [RESID (-1) ^2] is 0.0000 which is less than 1 percent and this indicates that the ARCH term is significant and therefore the ARCH term can predict volatility. Furthermore, it means that the return from the previous day affects the return for the current day. And the probability of the GARCH (-1) is 0.000 which is also less than 1 percent, therefore, the GARCH term is significant in predicting volatility, this points out that the conditional variance of the current day is affected by the variance of the previous day.

Table 5.2: The GARCH model for Capitec Bank Holding LTD

Mean Equation				
Variables	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001459	0.000324	4.509023	0.0000
AR (1)	0.200453	0.479345	0.418182	0.6758
MA (1)	-0.160390	0.482817	-0.332195	0.7397
Variance Equation				
C	1.51E-05	2.24E-06	6.722271	0.0000
RESID (-1)^2	0.085858	0.006696	1282320	0.0000
GARCH (-1)	0.864852	0.011950	72.37314	0.0000
R-Squared	0.000174	Akaike info criterion		-5.375518
Durbin-Watson stat	2.029837	Schwartz Criterion		-5.361521

Source: Eview output using Thomson Reuter Datastream (2019).

The top part of Table 5.2 is the ARIMA (1, 1, 1) results. The p-value for both AR and MA is more than 10 percent this means that ARIMA (1, 1, 1) model is not good for forecasting the mean stock prices for a differenced CPI when volatility is not taken into consideration. The bottom part of table 5.2 is the variance equation results and it can be written as follows:

σ^2 = 1.51E-05 - 0.085858u^2_{t-1} + 0.864852σ^2_{t-1}.. (5.2)

The probability of the ARCH term [RESID (-1) ^2] is 0.0000, this indicates that the ARCH term is significant and therefore the ARCH term can predict volatility. This means that the return from the previous day affects the return for the current day. And the probability of the

GARCH (-1) is 0.0000 which is less than 1 percent, therefore, the GARCH term is significant in predicting volatility in this model. Moreover, this points out that the conditional variance of the current day is affected by the variance of the previous day.

Table 5.3 GARCH model for Discovery LTD

Mean Equation				
Variables	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000915	0.000185	4.953628	0.0000
AR (1)	0.931683	0.033145	28.10970	0.0000
MA (1)	-0.952614	0.027618	-34.49201	0.0000
Variance Equation				
C	1.51E-06	4.61E-07	3.283664	0.0010
RESID (-1)^2	0.062077	0.005937	10.45612	0.0000
GARCH (-1)	0.934874	0.006080	153.7607	0.0000
R-Squared	0.005281	Akaike info criterion		-5.600077
Durbin-Watson stat	2.039341	Schwartz Criterion		-5.594996

Source: Eview output using Thomson Reuter Datastream (2019).

The upper part of Table 5.3 above shows ARIMA (1, 1, 1) results. The AR(1) and MA(1) have probabilities that are less than 1 percent, this implies that ARIMA (1, 1, 1) is good for forecasting the average share price for DSY but without including volatility. The bottom part of Table 5.3 shows the variance equation results which can be written as:

$\sigma^2 = 1.51E\text{-}06 - 0.062077u^2_{t-1} + 0.934874\sigma^2_{t-1}$…………………...……………………...…. (5.3)

The probability of the ARCH term is 0.0975 which is less than 1 percent and this indicates that the ARCH term is significant and therefore the ARCH term can predict volatility. This further implies that the return from the previous day affects the return for the current day. And the probability of the GARCH (-1) is 0.000 which is also less than 1 percent, therefore, the GARCH term is significant in predicting volatility in this model. Moreover, this points out that the conditional variance of the current day is affected by the variance of the previous day.

Table 5.4: The GARCH model for Kumba Iron Ore LTD

Mean Equation				
Variables	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000499	0.000481	1.037633	0.2994
AR (1)	-0.486773	0.740788	-0.657102	0.5111
MA (1)	0.498763	0.735351	0.678264	0.4976
Variance Equation				
C	4.97E-06	1.09E-06	4.570999	0.0000
RESID (-1)^2	0.055005	0.005488	10.02279	0.0000
GARCH (-1)	0.939792	0.004883	192.4485	0.0000
R-Squared	0.000473	Akaike info criterion		-4.414430
Durbin-Watson stat	1.994121	Schwartz Criterion		-4.400434

Source: Eview output using Thomson Reuter Datastream (2019).

Table 5.4 above has the probabilities of the AR (1) and MA (1) with values which are more than 10 percent this indicates that ARIMA (1, 1, 1) is not good for forecasting the average share price for KIO. The bottom part of Table 5.4 shows the variance equation results which can be written as:

$\sigma^2 = 4.97E\text{-}06 - 0.055005\, u^2_{t-1} + 0.939792\sigma^2_{t-1}$………………………………………… (5.4)

The probability of the ARCH term is zero this indicates that the ARCH term is significant at a 1 percent level and therefore the ARCH term can predict volatility. This indicates that the return from the previous day affects the return for the current day. And the probability of the GARCH (-1) is 0.0000 which shows that it is significant at a 1 percent level, at predicting volatility for KIO. Moreover, this points out that the conditional variance of the current day is affected by the variance of the previous day.

Table 5.5: The GARCH model for Mondi PLC

Mean Equation				
Variables	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001058	0.000312	3.389967	0.0007
AR (1)	0.607179	0.649182	0.935297	0.3496
MA (1)	-0.620604	0.640647	-0.968714	0.3327
Variance Equation				
C	2.53E-06	4.78E-07	5.302873	0.0000
RESID (-1)^2	0.01935	0.0003237	5.880696	0.0000
GARCH (-1)	0.971581	0.004154	233.5590	0.0000
R-Squared	-0.000149	Akaike info criterion		-5.312995
Durbin-Watson stat	1.997195	Schwartz Criterion		-5.298999

Source: Eview output using Thomson Reuter Datastream (2019).

Table 5.5 shows Mondi PLC GARCH results with the probability of the AR (1) and MA (1) which are more than 10 percent this indicates that ARIMA (1, 1, 1) is not good for forecasting the average share price for MNP. The bottom part of Table 5.5 shows the variance equation results which can be written as:

σ^2 =2.53E-06 -0.019035 u2t-1 + 0.971581σ^2t-1………………………………………. (5.5)

The probability of the ARCH term is 0.0000 this indicates that the ARCH model is significant at a 1 percent level and therefore it is good for forecasting volatility for MNP. And the probability of the GARCH (-1) is 0.0000 which is less than 1 percent, therefore, the GARCH term is significant in predicting volatility in this model. Moreover, this points out that the conditional variance of the current day is affected by the variance of the previous day.

Table 5.6: The GARCH model for Mr. Price Group LTD

Mean Equation				
Variables	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001269	0.000372	3.411326	0.0006
AR (1)	0.590004	0.517349	1.140436	0.2541
MA (1)	-0.600922	0.512085	-1.173481	0.2406
Variance Equation				
C	2.30E06	4.71E-07	4.896866	0.0000
RESID (-1)^2	0.024456	0.002209	11.06861	0.0000
GARCH (-1)	0.970761	0.002043	475.2185	0.0000
R-Squared	-0.000473	Akaike info criterion		-5.028941
Durbin-Watson stat	1.974807	Schwartz Criterion		-5.014944

Source: Eview output using IRESS SA (2019)

Table 5.6 above shows the GARCH results for Mr. Price Group LTD with AR (1) and MA (1) with probabilities which are more than 10 percent this implies that the ARIMA (1, 1, 1) is not good at forecasting the average share price for MRP. The bottom part of Table 5.6 shows the variance equation results which can be written as:

$\sigma^2 = 2.30E06 + 0.024456\ u^2_{t-1} + 0.970761\sigma^2 t\text{-}1$ .... (5.6)

The probability of the ARCH term is less than 1 percent and this indicates that the ARCH term is significant at predicting volatility for MRP. This means that the return from the previous day affects the return for the current day. And the probability of the GARCH (-1) is less than 1 percent therefore, the GARCH term is also significant at predicting volatility in this model

Table 5.7: The GARCH model for MTN Group LTD

Mean Equation				
Variables	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000234	0.000202	1.159078	0.2464
AR (1)	0.829325	0.043673	18.98932	0.0000
MA (1)	-0.897529	0.033142	-27.08136	0.0000
Variance Equation				
C	4.91E-06	9.25E-07	5.307383	0.0000
RESID (-1)^2	0.052914	0.004448	11.89612	0.0000
GARCH (-1)	0.936937	0.004986	187.9080	0.0000
R-Squared	0.008958	Akaike info criterion		-5.071282
Durbin-Watson stat	1.969040	Schwartz Criterion		-5.057286

Source: Eview output using IRESS SA (2019)

Table 5.7 above shows the probability of the AR (1) and MA (1) which is less than 1 percent this indicates that ARIMA (1, 1, 1) is good at forecasting the average share price for MTN. The bottom part of Table 5.7 shows the variance equation results which can be written as:

$\sigma^2 = 4.91E\text{-}06 + 0.052914u^2_{t-1} + 0.936937\sigma^2_{t-1}$…………………………………………… (5.7)

The probability of the ARCH term is 0.0000 that is less than 1 percent, this shows that the ARCH term is significant and therefore the ARCH term can predict volatility. This means that the return from the previous day affects the return for the current day. And the probability of the GARCH (-1) is 0.0000 that is less than 1 percent, therefore, the GARCH term is significant at predicting volatility in this model. Moreover, this points out that the conditional variance of the current day is affected by the variance of the previous day.

Table 5.8: The GARCH model for Naspers LTD

Mean Equation				
Variables	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001420	0.000297	4.782790	0.0000
AR (1)	0.767840	0.089934	8.537771	0.0000
MA (1)	-0.82852	0.079422	-10.33527	0.0000
Variance Equation				
C	9.85E-06	2.37E-06	4.148681	0.0000
RESID (-1)^2	0.057888	0.008026	7.213031	0.0000
GARCH (-1)	0.919106	0.011303	81.31204	0.0000
R-Squared	0.009003	Akaike info criterion		-4.992910
Durbin-Watson stat	2.001646	Schwartz Criterion		-4.978914

Source: Eview output using IRESS SA (2019)

The upper part of Table 5.8 is the ARIMA (1, 1, 1) results. The probability of the AR(1) and MA(1) is approximately close to zero, that is less than 1 percent this means that the ARIMA (1, 1, 1) model is good for forecasting the mean share for NPN but when volatility is not taken into consideration. The lower part of table 5.8 is the variance equation results. The variance equation can be expressed as:

$\sigma^2 = 0.000168 + 0.075615u^2_{t-1} + 0.834691\sigma^2_{t-1}$……………………………………………. (5.8)

The probability of the ARCH term is 0.000 this indicates that the ARCH term is significant at a 1 percent level and therefore the ARCH term can predict volatility. This means that the return from the previous day affects the return for the current day. And the probability of the GARCH (-1) is 0.0000 which implies that the GARCH term is significant at a 1 percent level. Moreover, this points out that the conditional variance of the current day is affected by the variance of the previous day.

Table 5.9: The GARCH model for Shoprite Holdings LTD

Mean Equation				
Variables	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000475	0.000286	1.660859	0.0967
AR (1)	0.623216	0.185486	3.359917	0.0008
MA (1)	-0.667589	0.176985	-3.772010	0.0002
Variance Equation				
C	1.26E-05	3.51E-06	3.582389	0.0003
RESID (-1)^2	0.047581	0.009147	5.201991	0.0000
GARCH (-1)	0.909185	0.018948	47.98329	0.0000
R-Squared	0.004431	Akaike info criterion		-5.340647
Durbin-Watson stat	1.988348	Schwartz Criterion		-5.326650

Source: Eview output using IRESS SA (2019)

Table 5.9 above shows the GARCH model for Shoprite Holdings LTD. The probability of AR (1) and MA (1) is less than 1 percent this indicates that ARIMA (1, 1, 1) model is good for forecasting the average share price for SHP but without including volatility. The bottom part table 5.9 shows the variance equation results which can be written as:

σ^2 = 1.26E-05-0.047581u^2_{t-1} + 0.909185σ^2_{t-1}………………………………………… (5.9)

The probability of the ARCH term is 0.0000 this indicates that the ARCH term is significant at a 1 percent level and therefore the ARCH term can predict volatility. When the ARCH term is significant it implies that the return from the previous day affects the return for the current day. And the probability of the GARCH (-1) is 0.0000 which means that the GARCH term is significant at a 1 percent level. Moreover, this points out that the conditional variance of the current day is affected by the variance of the previous day.

Table 5.10: The GARCH model for SASOL LTD

Mean Equation				
Variables	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000404	0.000314	1.286620	0.1982
AR (1)	-0.734848	0.125426	-5.858834	0.0000
MA (1)	0.777530	0.115599	6.726128	0.0000
Variance Equation				
C	3.04E-06	7.41E-07	4.108663	0.0000
RESID (-1)^2	0.049689	0.006340	7.836935	0.0000
GARCH (-1)	0.941041	0.007098	132.5798	0.0000
R-Squared	0.000992	Akaike info criterion		-5.312429
Durbin-Watson stat	2.065756	Schwartz Criterion		-5.298433

Source: Eview output using IRESS SA (2019)

Table 5.10 above shows the probability of AR (1) and MA (1) which is less than 1 percent, this indicates that ARIMA (1, 1, 1) is good for forecasting the average share price for SOL but without including volatility. The bottom part of Table 5.10 shows the variance equation results which can be written as:

$\sigma^2 = 3.04E\text{-}06 + 0.049689u^2_{t-1} + 0.941041\sigma^2_{t-1}$………………………………………. (5.10)

The probability of the ARCH term [RESID (-1) ^2] is zero, this indicates that the ARCH term is significant at a 1 percent level and therefore the ARCH term can predict volatility. This means that the return from the previous day affects the return for the current day. And the probability of the GARCH (-1) is 0.0000 this indicates that the GARCH term is significant at predicting volatility in this model. Moreover, this points out that the conditional variance of the current day is affected by the variance of the previous day.

5.3 Average Mean Returns

Section 5.3 shows results for the calculated average mean returns results. The average mean returns were used to analyze the potential benefits of market timing as part of an active portfolio management strategy. The mean return equation is shown below in equation 5.11. Where the superscript “c” is the continuous return and “h” is the holding period. The variables “C” and “O” are the closing and opening prices respectively (Tharavanij and Siraprapasiri, 2017). The mean returns were calculated based on the assumption that shares are held over a 4-day holding period and then sold at the closing price and were calculated before transaction costs.

$r^{c}_{t+h}=\ln C_{t+h}-\ln o_{t}$……….…………………………………………………….………(5.11)

When the mean return for a bullish candlestick pattern is positive it indicates that the pattern is “valid” or that it can give the correct signals about the market movements. For a bearish candlestick pattern to be valid its mean return must be negatively significant. Tables 5.11 to 5.20 below show the number of times a candlestick pattern was identified for each of the selected company and the average percentage return from those signals. Where n is the number of times the candlestick pattern appeared and M percent is the average percentage return.

Table 5.11: Aspen Pharmacy Holding Mean Returns

	Bullish Engulfing	Bearish Engulfing	Piercing Lines	Dark Cloud Cover	Hammer	Hanging Man	Shooting Star	Bullish Doji
n	23	104	8	9	116	134	208	39
M%	1,017	-0,580	-0.119	-2.130	1.241	-0.794	-1.567	-0.174

Source: Own calculations using data from Thomson Reuter Datastream (2019).

The hammer and the bullish engulfing’s average mean returns in percentage are positively significant this means that investors can make profits from using them. However, the other two bullish patterns, the bullish doji, and the piercing lines have a negative mean return which indicates that the use of these patterns when predicting Aspen pharmacy holding share prices is not useful. However, all the bearish candlestick signals: the shooting star, hanging man, bearish engulfing and the dark cloud cover are negatively significant this means that traders can make profits from selling when these patterns happen.

Table 5.12: Capitec Bank Holding LTD Mean Return

	Bullish Engulfing	Bearish Engulfing	Piercing Lines	Dark Cloud Cover	Hammer	Hanging Man	Shooting Star	Bullish Doji
n	29	76	7	12	169	161	169	126
M%	1,188	-0,520	-0,264	-0,257	1,437	-0,330	-1,070	0,753

Source: Own calculations using data from Thomson Reuter Datastream (2019).

The mean returns from the bearish engulfing, dark cloud cover, hanging man and the shooting star are negative this indicates that the selling signals given by these patterns were correct, therefore traders can benefit from using these bearish reversal patterns when making selling decisions for Capitec bank shares. The bullish engulfing, hammer and bullish doji are positively significant in predicting stock price movement; hence investors can generate higher returns on their investments on average by going long following these signals. However, the mean return for the piercing lines is negative which means that on average this pattern was giving false signals for Capitec bank shares.

Table 5.13: Discovery LTD Mean Return

	Bullish Engulfing	Bearish Engulfing	Piercing Lines	Dark Cloud Cover	Hammer	Hanging Man	Shooting Star	Bullish Doji
n	19	105	3	6	149	148	188	55
M%	1,3477	-0,8398	0,1294	0,7184	1,6494	-0,3455	-0,8997	0,2624

Source: Own calculations using data from Thomson Reuter Datastream (2019).

Table 5.13 above shows that bullish engulfing, bearish engulfing, piercing lines, hammer, hanging man, shooting star and bullish doji are statistically significant at predicting the price movement for Discovery LTD, but the dark cloud cover patterns are insignificant at predicting price movements for DSY.

Table 5.14: Kumba Iron Ore LTD Mean Return

	Bullish Engulfing	Bearish Engulfing	Piercing Lines	Dark Cloud Cover	Hammer	Hanging Man	Shooting Star	Bullish Doji
n	29	93	7	16	122	134	173	32
M%	1,594	-1,803	-0,235	3,651	2,064	-0,821	-1,782	-0,992

Source: Thomson Reuter Datastream (2019).

The bullish patterns: the bullish engulfing and the hammer are positively significant at predicting share price movements for KIO and the piercing lines and bullish doji do not predict KIO's future share prices correctly. The bearish reversal patterns, the bearish engulfing and shooting star correctly predicted that the prices were going down and the hanging man and the dark cloud cover did not correctly identify the price movement for KIO.

Table 5.15: Mondi PLC Mean Return

	Bullish Engulfing	Bearish Engulfing	Piercing Lines	Dark Cloud Cover	Hammer	Hanging Man	Shooting Star	Bullish Doji
n	32	69	12	15	108	105	182	28
M%	1,842	-1,502	0,780	0,863	1,846	-0,834	-1,037	-0,009

Source: Own calculations using data from Thomson Reuter Datastream (2019).

The average mean returns for the bullish reversal patterns: bullish engulfing, piercing lines and the hammer are positively significant this means that they give correct signals about the potential increase in the share prices for Mondi PLC, however, the bullish doji is not significant at predicting the share price movements for MNP. The bearish reversal patterns: the bearish engulfing, shooting star, and the hanging man are negatively significant at predicting stock price movements however the dark cloud cover does not give correct signals on average for MNP company.

Table 5.16: Mr Price Group LTD Mean Return

	Bullish Engulfing	Bearish Engulfing	Piercing Lines	Dark Cloud Cover	Hammer	Hanging Man	Shooting Star	Bullish Doji
n	28	90	6	10,	140	150	184	45
M%	1.428	-1.171	-0.071	2,600	2,077	-0,320	-1,326	0,645

Source: Own calculations using data from IRESS SA (2019)

The bullish engulfing, hammer and bullish doji give correct signals about the potential increase of Mr. Price Group LTD share prices. However, investors would have made a loss on average from following the piercing lines signals from 2009 to 2018. And the bearish reversal patterns: shooting star, bearish engulfing and the hanging man except the dark cloud cover are positively significant at predicting a drop of the MRP share prices.

Table 5.17: MTN Group LTD Mean Return

	Bullish Engulfing	Bearish Engulfing	Piercing Lines	Dark Cloud Cover	Hammer	Hanging Man	Shooting Star	Bullish Doji
n	22	103	6	13	111	135	170	24
M%	1,987	-0,705	0,321	-0,615	1,498	-0,541	-1,780	-0,539

Source: Own calculations using data from IRESS SA (2019)

The average mean returns for MTN Group LTD indicate that the bullish engulfing, piercing lines and the hammer are positively significant at providing the buy signals and the bullish doji is insignificant. On the other hand, all bearish reversal patterns namely: bearish engulfing, hanging man, shooting star and the dark cloud cover are negatively significant thus, investors who make trading decisions of MTN shares based on these patterns will make profits on average at least before transaction costs.

Table 5.18: Naspers LTD Mean Return

	Bullish Engulfing	Bearish Engulfing	Piercing Lines	Dark Cloud Cover	Hammer	Hanging Man	Shooting Star	Bullish Doji
n	30	84	11	14	142	149	139	21
M%	1,316	-0,206	0,430	0,432	1,877	-0,444	-1,438	0,309

Source: Own calculations using data from IRESS SA (2019)

All the bullish reversal patterns under this study gave correct signals about the price movement for Naspers LTD on average from 2009 to 2018 and the bearish patterns: bearish engulfing, hanging man and the shooting star except the dark cloud cover were negatively significant at identifying the price movements for NPN.

Table 5.19: Shoprite Holdings LTD Mean Return

	Bullish Engulfing	Bearish Engulfing	Piercing Lines	Dark Cloud Cover	Hammer	Hanging Man	Shooting Star	Bullish Doji
n	33	104	7	11	130	141	197	28
M%	1,606	-0,957	-2,290	1,579	1,598	-0,494	-1,391	0,181

Source: Own calculations using data from IRESS SA (2019)

The mean returns from Shoprite Holdings LTD indicate that the bullish engulfing, hammer and the bullish doji patterns are positively significant at predicting share price movement for SHP and the piercing lines are insignificant. The bearish patterns: shooting star, bearish engulfing, and hanging man except the dark cloud cover are negatively significant in predicting a potential decrease in SHP share prices.

Table 5.20: SASOL LTD Mean Return

	Bullish Engulfing	Bearish Engulfing	Piercing Lines	Dark Cloud Cover	Hammer	Hanging Man	Shooting Star	Bullish Doji
n	19	78	5	13	138	157	191	22
M%	1,452	-0,885	1,702	0,427	1,392	-0,813	-1,375	-0,804

Source: Own calculations using data from IRESS SA (2019)

The bullish engulfing, piercing lines and the hammer patterns are positively significant at predicting the share prices for SOL however the bullish doji is insignificant. The bearish reversal patterns: the shooting star, hanging man and the bearish engulfing are negatively significant at forecasting the share prices for SOL however the dark cloud cover patterns are insignificant which indicates that on average investors who follows the dark cloud cover patterns when making the trading decisions for SASOL will make a loss.

5.4. Binomial Tests

Tables 5.21 to 5.30 below show the results of the binomial tests for a ten years period, starting from 02 January 2009 to 31 December 2018, with a sample of 2498 observations. These calculations were based on a four days holding period. Each table shows the binomial test for all the candlestick patterns and on each company analyzed under this study.

Binomial Test = nC/N……………………………………………...………………..…(5.12)

Equation 5.12 above shows the binomial test function. The binomial test calculates the probability of getting the correct signals from the candlestick patterns and is calculated by dividing nC by N (Tharavanij and Siraprapasiri, 2017). Where nC is the total number of correct signals and N is the total number of observed signals. If the probability value is more than 0.5 it indicates that the candlestick pattern can predict the future short-term returns and when the probability value is not more than 0.5 it indicates that the candlestick pattern does not have the predictive power.

Table 5.21: Binomial Test for Aspen Pharmacy Holding

	Bullish Engulfing	Bearish Engulfing	Piercing Lines	Dark Cloud Cover	Hammer	Hanging Man	Shooting Star	Bullish Doji
nC	16	59	5	7	82	81	140	17
n	23	104	8	9	116	134	208	39
Probability	0.6957	0.5673	0.625	0.7778	0.7069	0.6045	0.6731	0.4359

Source: Own calculations using data from Thomson Reuter Datastream (2019).

In Table 5.21 above, all the identified candlestick patterns except the bullish doji have probability values that are more than 0.5, this means that these candlestick patterns can successfully predict the future short term returns for APN. However, since the bullish doji has a probability value that is less than 0.5 it means that it is unsuccessful at forecasting the price movement for the APN company. These results are very similar to the results from the mean returns on Table 5.11 above. For instance, on Table 5.11 the mean returns for the dark cloud cover is negative which mean that the dark cloud cover can predict the downtrend of the APN firm and these results are supported by the binomial test results because the probability value of the dark cloud is above 0.5 which is approximately 78 percent this means that on average the likelihood of getting the correct signals from the dark cloud cover is about 78 percent.

Table 5.22: Binomial Test for Capitec Bank Holding LTD

	Bullish Engulfing	Bearish Engulfing	Piercing Lines	Dark Cloud Cover	Hammer	Hanging Man	Shooting Star	Bullish Doji
nC	17	44	2	7	123	83	107	80
n	29	76	7	12	169	161	169	126
Prob	0,5862	0,5790	0,2858	0,5833	0,7278	0,5155	0,6331	0,6350

Source: Own calculations using data from Thomson Reuter Datastream (2019).

All the bearish reversal patterns show that they are capable of predicting the stock price movement for CPI. On the other hand, the three bullish reversal patterns the bullish engulfing, hammer and the bullish doji proved to have the predictive power on CPI share prices since their probability values are more than 0.5. However, the probability value of the piercing lines is less than 0.5 this means that the piercing lines cannot predict the share price movements of CPI successfully. These results confirm the above mean returns results on the table above (Table 5.12).

Table 5.23: Binomial Test for Discovery LTD

	Bullish Engulfing	Bearish Engulfing	Piercing Lines	Dark Cloud Cover	Hammer	Hanging Man	Shooting Star	Bullish Doji
nC	14	66	2	2	113	80	123	27
n	19	105	3	6	149	148	188	55
Prob	0,7368	0,6286	0,6667	0,3333	0,7584	0,5405	0,6543	0,4909

Source: Own calculations using data from Thomson Reuter Datastream (2019).

The binomial test results above in Table 5.23 are based on DSY data. These results indicate that all the candlestick patterns except the dark cloud cover and the bullish doji are significant, hence they can predict the short term returns for DSY. These results are very similar to the mean return results given in Table 5.13 above except that the mean returns generated from following the bullish doji signals generated a positive return. This means that even though the likelihood of getting the correct signals from the bullish doji is about 49 percent it managed to generate positive returns to traders at least before transaction costs were taken into account.

Table 5.24: Binomial Test for Kumba Iron Ore LTD

	Bullish Engulfing	Bearish Engulfing	Piercing Lines	Dark Cloud Cover	Hammer	Hanging Man	Shooting Star	Bullish Doji
nC	21	58	5	3	90	77	108	15
n	29	93	7	16	122	134	173	32
Prob	0,7241	0,6237	0,7143	0,1875	0,7377	0,5746	0,6243	0,4688

Source: Own calculations using data from Thomson Reuter Datastream (2019).

The binomial test results for the candlestick patterns based on KIO data are very similar to those given above in Table 5.23 for the DSY Company. These results show that only the dark cloud cover and the bullish doji patterns are insignificant, which means that they cannot predict short term return for KIO successfully, whereas the other candlestick patterns were significant at predicting the short term returns for KIO.

Table 5.25: Binomial Test for Mondi PLC

	Bullish Engulfing	Bearish Engulfing	Piercing Lines	Dark Cloud Cover	Hammer	Hanging Man	Shooting Star	Bullish Doji
nC	27	48	6	6	76	62	114	11
n	32	69	12	15	108	105	182	28
Prob.	0,8438	0,6957	0,5	0,4	0,7037	0,5905	0,6264	0,3929

Source: Own calculations using data from Thomson Reuter Datastream (2019).

The probability value of the bullish engulfing, bearish engulfing, hammer, hanging man and the shooting star is more than 0.5 percent, this indicates that more than half of the times these patterns are able to predict the short term returns for Mondi PLC. However, the dark cloud cover and the bullish doji have the probability values that are less than 0.5 and these patterns were also found to have not generated a positive profit when the mean returns for Mondi PLC were calculated in table 5.15.

Table 5.26: Binomial Test for Mr. Price Group LTD

	Bullish Engulfing	Bearish Engulfing	Piercing Lines	Dark Cloud Cover	Hammer	Hanging Man	Shooting Star	Bullish Doji
nC	18	54	3	1	100	77	118	28
n	28	90	6	10	140	150	184	45
Prob	0,6429	0,6	0,5	0,1	0,7143	0,5133	0,6413	0,6222

Source: Own calculations using data from IRESS SA (2019)

The binomial test results above indicate that all the candlestick reversal patterns except the piercing lines and the dark cloud cover are significant, which means that they can predict the short term returns for Mr. Price LTD. These results confirm the mean returns results which are given above in Table 5.16.

Table 5.27: Binomial Test for MTN Group LTD

	Bullish Engulfing	Bearish Engulfing	Piercing Lines	Dark Cloud Cover	Hammer	Hanging Man	Shooting Star	Bullish Doji
nC	17	59	3	7	80	78	117	10
n	22	103	6	13	111	135	170	24
Prob	0,7727	0,5728	0,5	0,5385	0,7207	0,5778	0,6882	0,4167

Source: Own calculations using data from IRESS SA (2019)

Table 5.27 above shows that the probability value of the piercing lines and the bullish doji is less than 0.5. This implies that the piercing lines and the bullish doji cannot predict the short term returns for MTN successfully. On the other hand, the binomial test results show that all the reversal patterns are significant and therefore can reliably predict MTN's share price movements.

Table 5.28: Binomial Test for Naspers LTD

	Bullish Engulfing	Bearish Engulfing	Piercing Lines	Dark Cloud Cover	Hammer	Hanging Man	Shooting Star	Bullish Doji
nC	21	46	7	6	106	78	94	9
n	30	84	11	14	142	149	139	21
Prob	0,7	0,5476	0,6364	0,4286	0,7465	0,5235	0,6763	0,4286

Source: Own calculations using data from IRESS SA (2019)

The binomial tests based on Naspers LTD (NPN) data on table 5.28 above show that the bearish engulfing, hanging man, shooting star, bullish engulfing, piercing lines and the hammer are statistically significant, which mean that they can predict NPN short term returns. On the other hand, the dark cloud cover and the bullish doji are statistically insignificant which means that they cannot reliably predict short term returns for NPN successfully.

Table 5.29: Binomial Test for Shoprite Holdings LTD

	Bullish Engulfing	Bearish Engulfing	Piercing Lines	Dark Cloud Cover	Hammer	Hanging Man	Shooting Star	Bullish Doji
nC	22	67	0	2	95	74	139	11
n	33	104	7	11	130	141	197	28
Prob	0,6667	0,6442	0	0,1818	0,7308	0,5248	0,7056	0,3929

Source: Own calculations using data from IRESS SA (2019)

The binomial test above in table 5.29 above shows that the probability value of the piercing lines, dark cloud cover and the bullish doji is not more than 0.5 this means that these patterns are insignificant at predicting the short term returns for SHP, on the other hand, the bullish engulfing, bearish engulfing, hammer and the hanging man patterns are statistically significant at predicting short term returns for SHP.

Table 5.30: Binomial Test for SASOL LTD

	Bullish Engulfing	Bearish Engulfing	Piercing Lines	Dark Cloud Cover	Hammer	Hanging Man	Shooting Star	Bullish Doji
nC	14	50	4	6	101	96	131	10
n	19	78	5	13	138	157	191	22
Prob	0,7368	0,6410	0,8	0,4615	0,7319	0,6115	0,6859	0,4545

Source: Own calculations using data from IRESS SA (2019)

Table 5.30 above shows the binomial test results for the eight candlestick patterns analyzed under this study based on SOL data. The results indicate that all the identified candlestick patterns except the dark cloud cover and the bullish doji are statistically significant. These results are very similar to the binomial test results of Naspers LTD which are given in Table 5.28.

5.5 Summary

The Eviews GARCH results from this study show that the probability value of the ARCH and GARCH term for all the companies is significant. These findings are similar to the results of Khan and Abdullah (2018) and Effendi (2015). This indicates that the returns from the previous day affect the returns for the current day. Therefore there is a positive correlation between the past share prices and future share prices. After examining the eight candlestick patterns: the bullish engulfing, piercing lines, hammer, hanging man, shooting star, bullish doji, bearish engulfing pattern and the dark cloud cover pattern. The study discovered that five of the candlestick patterns are statistically significant and these patterns are the shooting star, hanging man, bearish engulfing, bullish hammer and bullish engulfing patterns. On the other hand, the results discovered that three candlestick patterns are statistically insignificant and these patterns are the dark cloud cover, piercing lines and the bullish doji. This study discovered that the Japanese candlestick patterns are useful tools of technical analysis and therefore investors can use them when forecasting stock prices. These results are consistent and similar to the results of Do Prado, Fernada, Luiz, and Matsura (2013) and Ameen (2013).

CHAPTER 6

CONCLUSION AND RECOMMENDATIONS

6.1 Introduction

This research investigates the ongoing investment debate which is that the equity market is efficient and therefore active investors cannot outperform the market. To answer this, the paper begins by investigating the correlation between the previous share prices and future share prices by making use of the GARCH model. This is aimed to assess if the use of past share price data can be useful when making predictions about the market movements. This research also analyses the potential benefits from the candlestick patterns by making use of the binomial test and by calculating the potential mean returns. The mean returns were calculated to check if a particular candlestick pattern can predict the price movement for a particular company. The bullish candlestick patterns can give correct signals about the market movement when the mean returns are positively significant and the bearish candlestick patterns are effective when their mean returns are negatively significant. The binomial test calculates the probability value, and if this probability value is more than 0.5 it indicates that the pattern can predict the short term returns.

The study examined ten companies with eight candlestick patterns. And these companies are Aspen Pharmacy Holding (APN), Capitec Bank Holding LTD (CPI), Discovery LTD (DSY), Kumba Iron Ore LTD (KIO), Mondi PLC (MNP), Mr. Price Group LTD (MRP), MTN Group LTD (MTN), Naspers LTD (NPN), SASOL LTD (SOL) and Shoprite Holdings LTD (SHP). The eight candlestick reversal patterns, four are bullish patterns namely: doji start, hammer, bullish engulfing and the piercing lines patterns and the other four are bearish patterns which are the shooting star, hanging man, bearish engulfing and the dark cloud cover patterns.

6.2. Literature Review and Method

To understand the market timing and portfolio returns, the literature review was conducted in chapter 3. The literature review started by providing a revision on existing studies on the use of candlestick patterns and then discusses existing literature on the GARCH models in modeling volatility. Finally, the existing literature on passive versus active management and the efficient market hypothesis was discussed. Chapter 3 shows that several existing studies such as Zawali, Safiih, and Anthea (2011), Mtemeri (2009) and Masinga, 2016) support the GARCH (1, 1) model and that it is effective when used to estimate the conditional variance in the short term. However, the literature review shows mixed results on the usefulness of the Japanese candlestick patterns when used to forecast securities' prices. Existing literature also shows that there are no confirmed laws in finance about how the market works, therefore when active and passive investing is compared the results are mixed; hence existing literature shows that there is no clear answer on which investment method is better between these strategies.

Chapter 4 outline the analytical approach used in this study. The chapter began by providing a discussion of the research paradigm, followed by the research design. This study used the GARCH (1, 1) model to test the correlation between historical share prices and future share prices. The GARCH (1, 1) was selected because several existing literature supports this model and that it is efficient and effective when it is applied to short term data. The candlestick patterns used in this study are the bullish doji, hammer, bullish engulfing, piercing lines, shooting star, hanging man, bearish engulfing and the dark cloud cover. These patterns were selected because existing literature shows that they are common and are considered major reversal patterns. Another reason for including them was because there are not many mathematical definitions of the candlestick patterns in the existing literature. They can, therefore, be used scientifically by specifying formulas/functions in Excel. And to test for the effectiveness of the candlestick patterns the mean returns and the binomial tests were computed.

6.2 Key Findings

The GARCH (1, 1) results on chapter 5 indicate that there is a serial correlation between the returns of the previous day and the returns of the current day. The ARCH term (RESID(-1)^2) is significant in all the companies analyzed under this study. Therefore, this indicates that the return from the previous day affects the return for the current day. The GARCH term is also significant in predicting the volatility of all the companies and this means that the conditional variance of the current day is influenced by the previous day's variance. Moreover, for all companies under this study, the sum of the ARCH and GARCH coefficients is less than 1 this shows that there is a mean-reverting variance process, and the sum is close to the value 1 which indicates that the process mean reverts slowly.

The study discovered that most of the candlestick signal is from the bearish reversal patterns. The study identified that 67 percent of the candlestick signals were from the bearish reversal patterns. The mean returns for the shooting star, hanging man and the bearish engulfing for all the ten companies were negatively significant which means that investors can make profits by selling when these patterns appear. The binomial test results confirmed these results, since the probability value for the shooting star, hanging man and the bearish engulfing patterns were more than 0.5 for all the ten companies analyzed in this study.

However, the results show that the signals from the dark cloud cover were not useful and that the dark cloud cover cannot predict the share prices successfully. This is because its mean returns are significant in four companies out of ten. These results are supported by the binomial test results which show that the probability of getting the correct signals from the dark cloud cover is more than 0.5 in three companies out of ten. And this indicates that the dark cloud cover cannot predict the short term returns successfully.

The study identified 33 percent of the signals from the bullish reversal patterns. The mean returns for the bullish engulfing and the hammer patterns were found to be positively significant in all ten companies investigated in this study. This means that investors would make profits from using these patterns when making trading decisions. The binomial test results confirm these results since their probability values are more than 0.5 in all companies which means that on average these patterns able to predict short term returns.

The results revealed that there is no evidence that the piercing lines and the bullish doji can give correct signals across all ten companies. This is because the mean returns for the piercing lines and the bullish doji patterns were significant only in five companies out of ten. These results are supported by the results from the binomial tests, since the probability of the piercing lines with values that are more than 0.5 was only identified in five companies out of ten. On the other hand, only two out of ten companies had a probability value that is more than 0.5 from the bullish doji.

6.3 Limitations and Future Implications

This paper analyses the symmetric effect of volatility by implementing the GARCH model however in real life the symmetric effect assumption is often violated. To solve this issue the EGARCH, TGARCH BGARCH and PGARCH may be used in order to have a clearer view of volatility. Another limitation is that this paper investigates the behavior of share prices using ten companies only and the profitability of the candlestick patterns is evaluated using eight Japanese candlestick reversal patterns. Further studies could improve results by adding the number of companies and the number of the candlestick patterns analyzed. Moreover, future studies should analyze the candlestick reversal patterns when they are used with other trading rules such as oscillators and support resistance levels.

6.4 Conclusion

The value of market timing as part of an active portfolio management strategy is a major debate that exists in the finance community. This paper contributes to the literature by analyzing the potential benefits of market timing as part of an active portfolio management strategy. To do this the paper test for correlation between past share prices and future share prices using the GARCH model and used the binomial test together with the mean returns calculations to test if the Japanese candlestick patterns can add value to traders. The GARCH test results found that there is a strong positive correlation between the past share prices and future share prices. This positive correlation was identified in all the companies assessed in this study.

After assessing eight candlestick patterns in ten companies from the JSE top 40. The study discovered that the results from the binomial test and the mean returns calculations provides strong evidence that the shooting star, hanging man, bearish engulfing, bullish hammer and the bullish engulfing patterns are statistically significant, and therefore these patterns can predict short term returns and are able to assist investors when forecasting share prices. Moreover, based on the mean returns results and the binomial tests also discovered that the dark cloud cover, piercing lines, and the bullish doji cannot reliably predict the short term market movements and therefore cannot benefits investors who use these signals when trading. Since five out of eight candlestick patterns were statistically significant it is concluded that some candlestick patterns can give the correct signals about future price movements. In a nutshell, this study found that candlestick patterns of technical analysis can predict share prices. Therefore investors can make abnormal profits from using this technique.

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8. APPENDICES

APPENDIX A

Table A1: APN Augmented Dickey-Fuller Unit Root Test

APN	t-Statistics Level Terms	Prob.* Level Terms	t-Statistics Level First difference	Prob.* First difference
Augmented Dickey-Fuller test statistic	-1.4889	0.5393	-50.3342	0.0001
Critical value: 1%	-3.4328		-3.4328	
Critical value: 5%	-2.8625		-2.8625	
Critical value: 10%	-2.5673		-2.5673	

Source: Eview output using Thomson Reuter Datastream (2019).

Table A2: CPI Augmented Dickey-Fuller Unit Root

CPI	t-Statistics Level Terms	Prob.* Level Terms	t-Statistics First difference	Prob.* First difference
Augmented Dickey-Fuller test statistic	0.8079	0.9942	-50.5318	0.0001
Critical value: 1%	-3.4328		-3.4328	
Critical value: 5%	-2.8623		-2.8625	
Critical value: 10%	-2.5673		-2.5673	

Source: Eview output using Thomson Reuter Datastream (2019).

Table A3: DSY Augmented Dickey-Fuller Unit Root Test

DSY	t-Statistics	Prob.* Level Terms	t-Statistics First difference	Prob.* First difference
Augmented Dickey-Fuller test statistic	-0.7995	0.8186	-51.5787	0.0001
Critical value: 1%	-3.4328		-3.4328	
Critical value: 5%	-2.8624		-2.8625	
Critical value: 10%	-2.5673		-2.5673	

Source: Eview output using Thomson Reuter Datastream (2019).

Table A4: KIO Augmented Dickey-Fuller Unit Root Test

KIO	t-Statistics	Prob.* Level Terms	t-Statistics First difference	Prob.* First difference
Augmented Dickey-Fuller test statistic	-1.4761	0.5458	-51.0260	0.0001
Critical value: 1%	-3.4328		-3.4328	
Critical value: 5%	-2.8625		-2.8625	
Critical value: 10%	-2.5673		-2.5673	

Source: Eview output using Thomson Reuter Datastream (2019).

Table A5: MNP Augmented Dickey-Fuller Unit Root Test

MNP	t-Statistics	Prob.* Level Terms	t-Statistics First difference	Prob.* First difference
Augmented Dickey-Fuller test statistic	-0.8573	0.8019	-51.4879	0.0001

Critical value: 1%	-3.4328		-3.4328	
Critical value: 5%	-2.8625		-2.8625	
Critical value: 10%	-2.5673		-2.5673	

Source: Eview output using Thomson Reuter Datastream (2019).

Table A6: MRP Augmented Dickey-Fuller Unit Root Test

MRP	t-Statistics	Prob.* Level Terms	t-Statistics First difference	Prob.* First difference
Augmented Dickey-Fuller test statistic	-1.2469	0.6560	-51.6479	0.0001
Critical value: 1%	-3.4328		-3.4328	
Critical value: 5%	-2.8625		-2.8625	
Critical value: 10%	-2.5673		-2.5673	

Source: Eview output using IRESS SA (2019)

Table A7: MTN Augmented Dickey-Fuller Unit Root Test

MTN	t-Statistics	Prob.* Level Terms	t-Statistics First difference	Prob.* First difference
Augmented Dickey-Fuller test statistic	-1.3581	0.6042	-39.5156	0.0000
Critical value: 1%	-3.4328		-3.4328	
Critical value: 5%	-2.8625		-2.8625	
Critical value: 10%	-2.5673		-2.5673	

Source: Eview output using IRESS SA (2019)

Table A8: NPN Augmented Dickey-Fuller Unit Root Test

NPN	t-Statistics	Prob.* Level Terms	t-Statistics First difference	Prob.* First difference
Augmented Dickey-Fuller test statistic	-0.5758	0.8735	-48.7880	0.0001

Critical value: 1%	-3.4328		-3.4328	
Critical value: 5%	-2.8625		-2.8625	
Critical value: 10%	-2.5673		-2.5673	

Source: Eview output using IRESS SA (2019)

Table A9: SHP Augmented Dickey-Fuller Unit Root Test

SHP	t-Statistics	Prob.* Level Terms	t-Statistics First difference	Prob.* First difference
Augmented Dickey-Fuller test statistic	-1.8965	0.3343	-51.9837	0.0001
Critical value: 1%	-3.4328		-3.4328	
Critical value: 5%	-2.8625		-2.8625	
Critical value: 10%	-2.5673		-2.5673	

Source: Eview output using IRESS SA (2019)

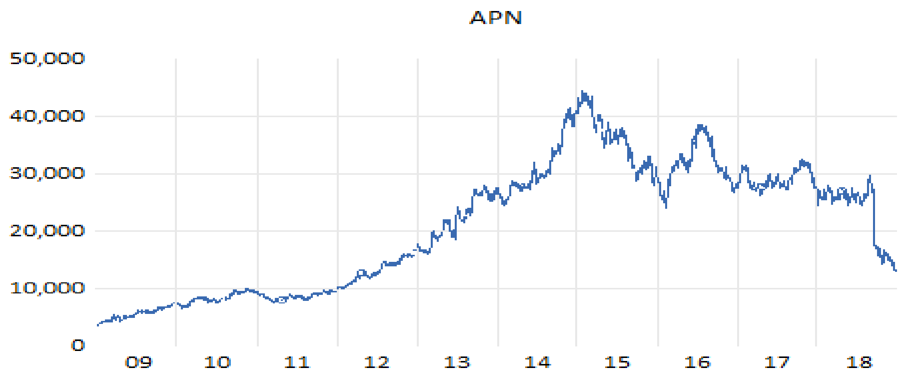
Table A10: SOL Augmented Dickey-Fuller Unit Root Test

SOL	t-Statistics	Prob.* Level Terms	t-Statistics First difference	Prob.* First difference
Augmented Dickey-Fuller test statistic	-2.0588	0.2618	-38.3330	0.0000
Critical value: 1%	-3.4328		-3.4328	
Critical value: 5%	-2.8662		-2.8625	
Critical value: 10%	-2.5673		-2.5673	

Source: Eview output using IRESS SA (2019)

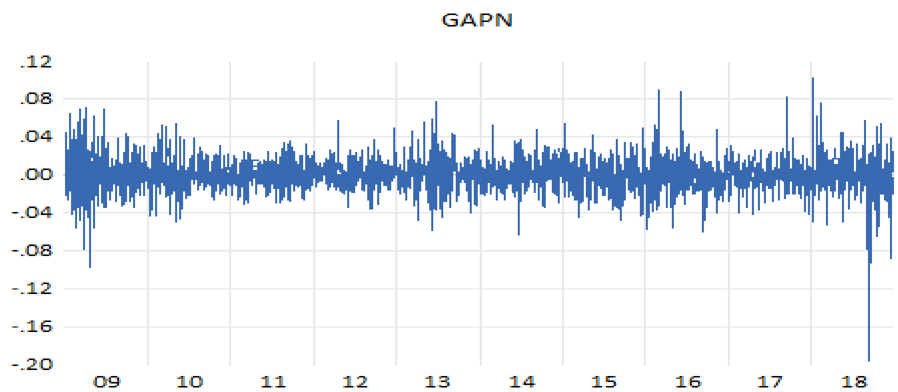
APPENDIX B

Figure B1: APN in level terms



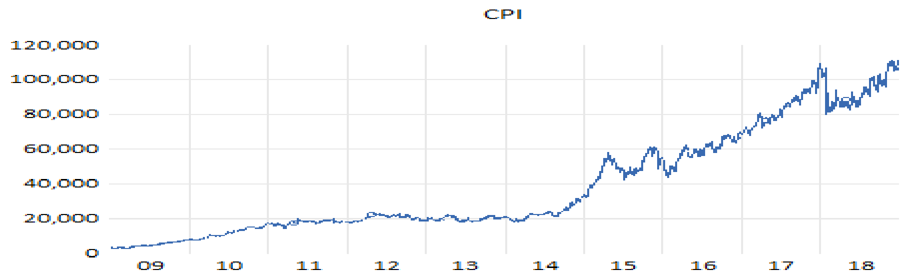
Source: Eview output using Thomson Reuter Datastream (2019).

Figure B2: APN in First Difference



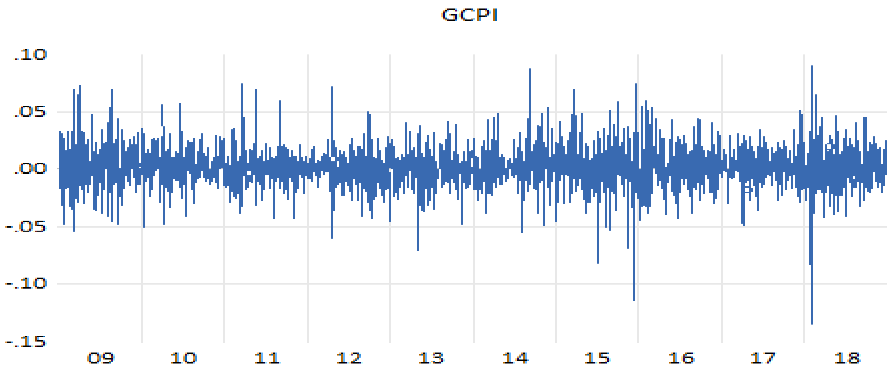
Source: Eview output using Thomson Reuter Datastream (2019).

Figure B3: CPI in level terms



Source: Eview output using Thomson Reuter Datastream (2019).

Figure B4: CPI in First Difference

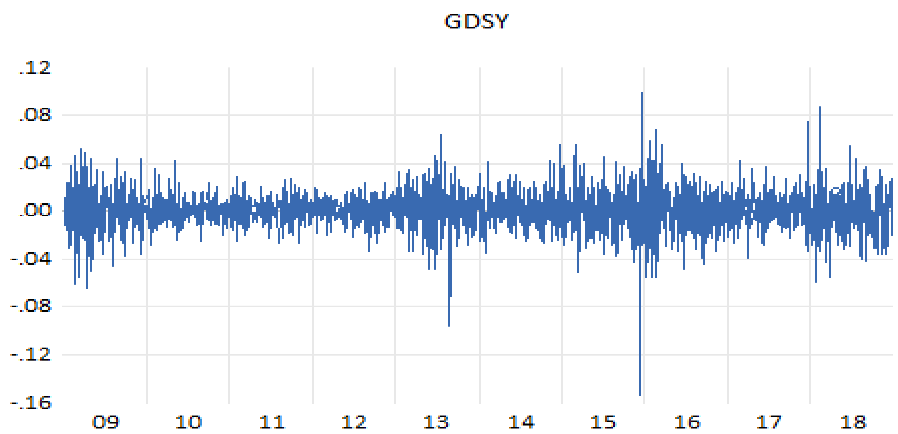


Source: Eview output using Thomson Reuter Datastream (2019).

Figure B5: DSY in Level Terms

Source: Eview output using Thomson Reuter Datastream (2019)

Figure B6: DSY in First Difference

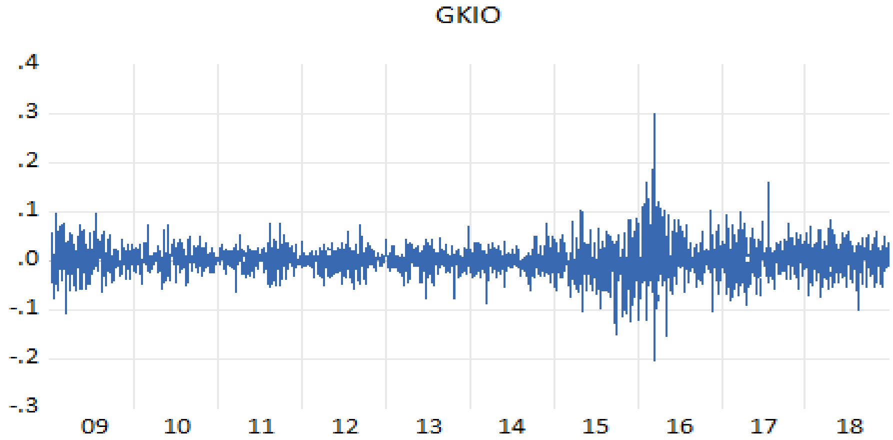


Source: Eview output using Thomson Reuter Datastream (2019).

Figure B7: KIO in Level Terms

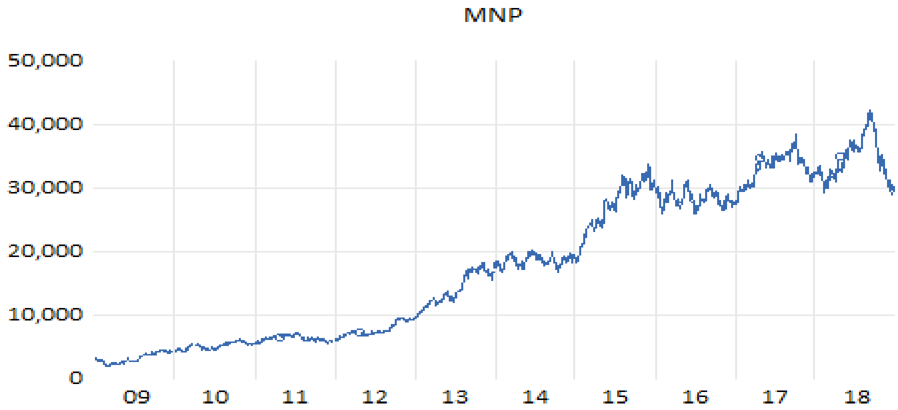
Source: Eview output using Thomson Reuter Datastream (2019).

Figure B8: KIO in First Difference



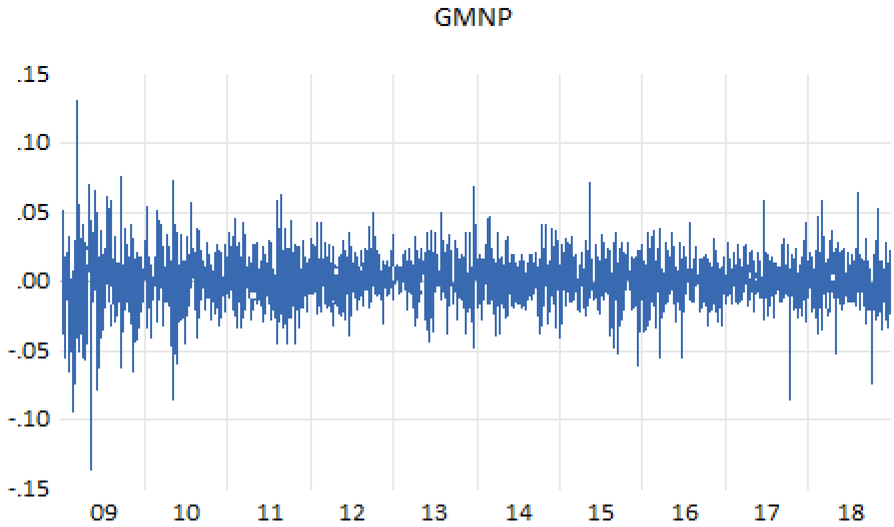
Source: Eview output using Thomson Reuter Datastream (2019).

Figure B9: MNP in Level Terms



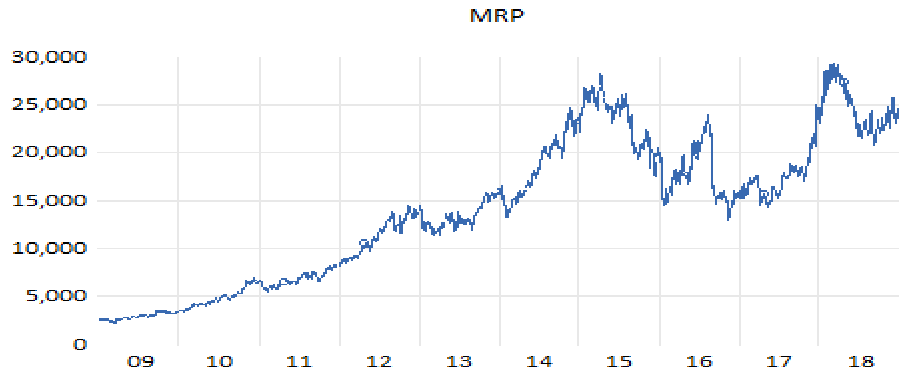
Source: Eview output using Thomson Reuter Datastream (2019).

<u>Figure B10: MNP in First Difference</u>



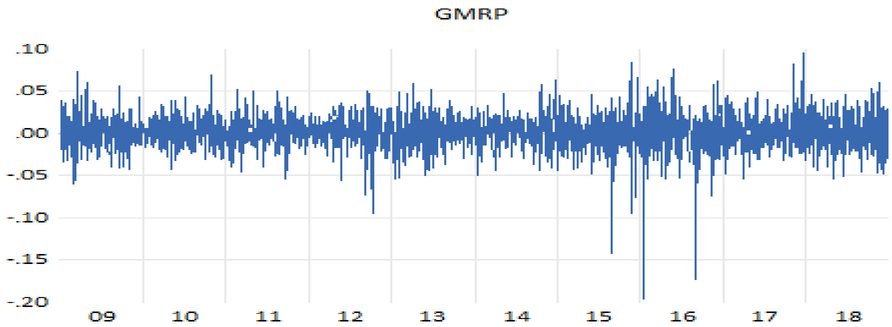
Source: Eview output using Thomson Reuter Datastream (2019).

Figure B11: MRP in Level Terms



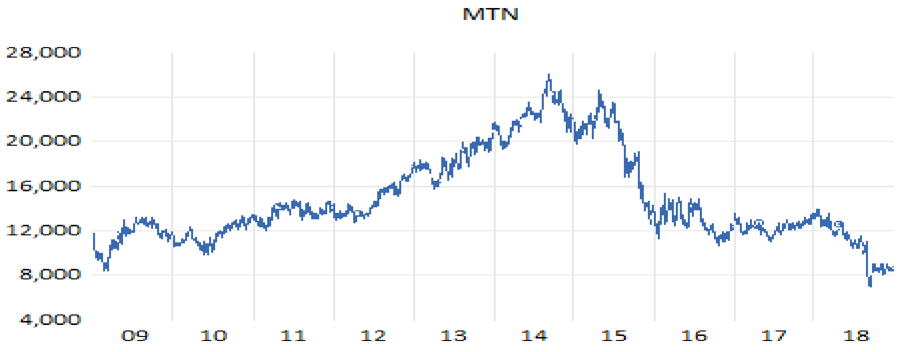
Source: Eview output using IRESS SA (2019)

Figure B12: MRP in First Difference



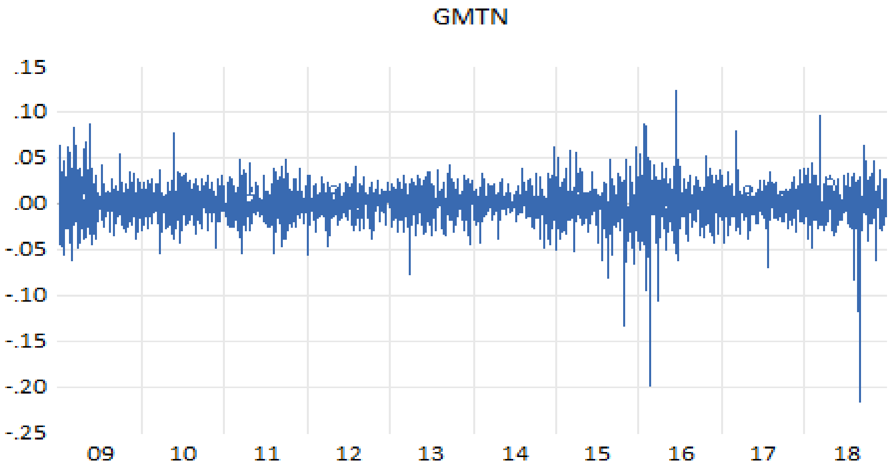
Source: Eview output using IRESS SA (2019)

Figure B13: MTN in Level Terms



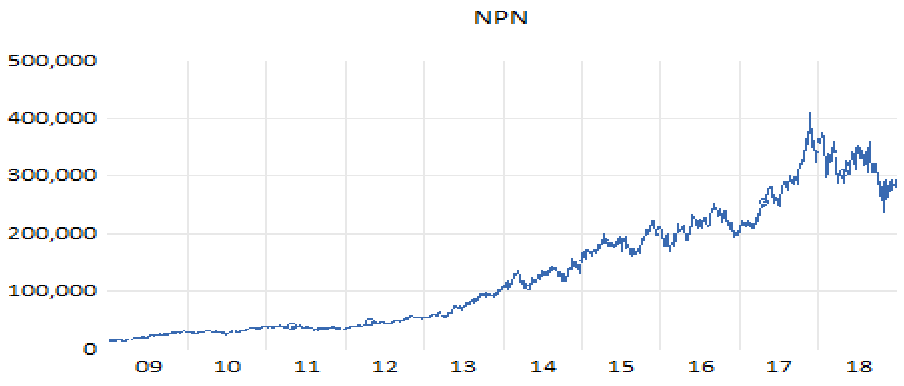
Source: Eview output using IRESS SA (2019)

Figure B14: MTN in First Difference



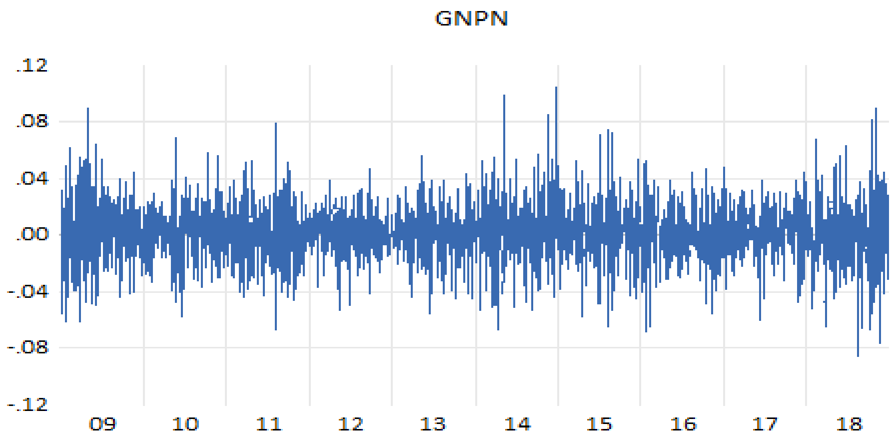
Source: Eview output using IRESS SA (2019)

Figure B15: NPN in Level Terms



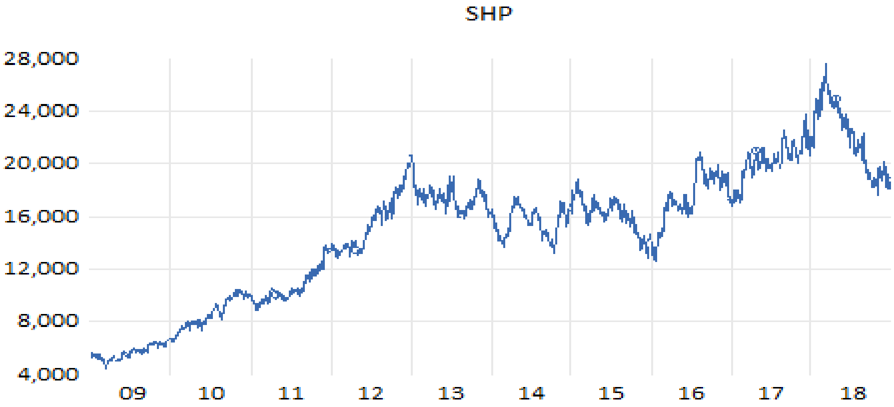
Source: Eview output using IRESS SA (2019)

Figure B16: NPN in First Difference



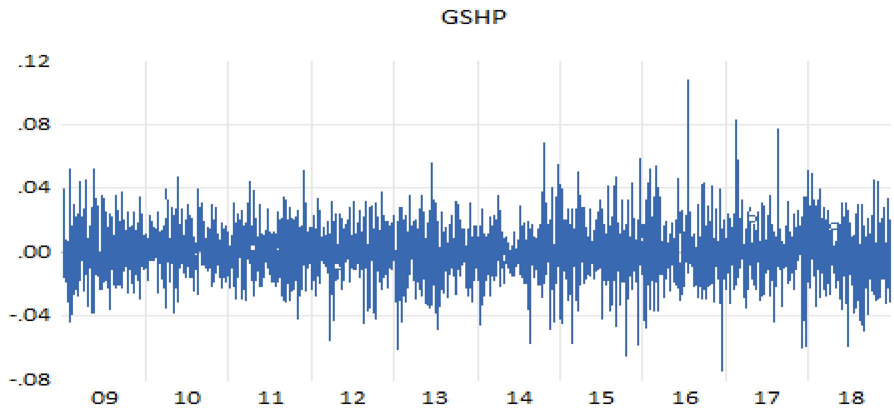
Source: Eview output using IRESS SA (2019)

Figure B17: SHP in Level Terms



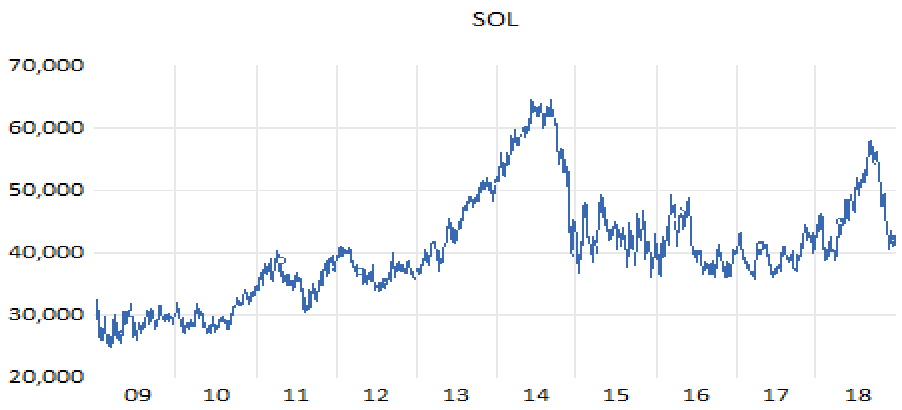
Source: Eview output using IRESS SA (2019)

Figure B18: SHP in First Difference



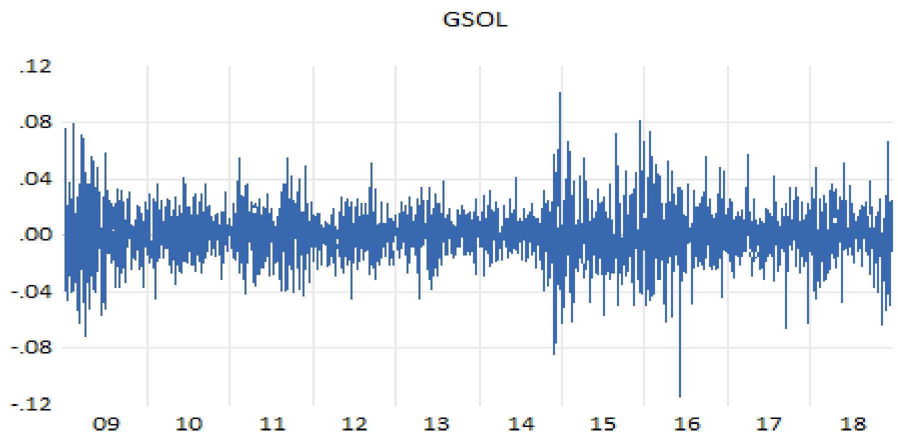
Source: Eview output using IRESS SA (2019)

Figure B19: SOL in Level Terms



Source: Eview output using IRESS SA (2019)

Figure B20: SOL in First Difference



Source: Eview output using IRESS SA (2019)

APPENDIX C

Table C1: Heteroskedasticity Test: APN ARCH test

F-statistics	355.6644	Prob. F (1.2494)	0.0000
Obs*R-squared	311.5238	Prob. Chi-Square (1)	0.0000

Source: Eview output using Thomson Reuter Datastream (2019).

Table C2: Heteroskedasticity Test: CPI ARCH test

F-statistics	106.8924	Prob. F (1.2494)	0.0000
Obs*R-squared	102.5815	Prob. Chi-Square (1)	0.0000

Source: Eview output using Thomson Reuter Datastream (2019).

Table C3: Heteroskedasticity Test: DSY ARCH test

F-statistics	32.44314	Prob. F (1.2494)	0.0000
Obs*R-squared	32.05221	Prob. Chi-Square (1)	0.0000

Source: Eview output using Thomson Reuter Datastream (2019).

Table C4: Heteroskedasticity Test: KIO ARCH test

F-statistics	262.2643	Prob. F (1.2494)	0.0000
Obs*R-squared	237.4996	Prob. Chi-Square (1)	0.0000

Source: Eview output using Thomson Reuter Datastream (2019).

Table C5: Heteroskedasticity Test: MNP ARCH test

F-statistics	51.01769	Prob. F (1.2494)	0.0000
Obs*R-squared	50.03508	Prob. Chi-Square (1)	0.0000

Source: Eview output using Thomson Reuter Datastream (2019).

Table C6: Heteroskedasticity Test: MRP ARCH test

F-statistics	19.73747	Prob. F (1.2494)	0.0000
Obs*R-squared	19.59820	Prob. Chi-Square (1)	0.0000

Source: Eview output using IRESS SA (2019)

Table C7: Heteroskedasticity Test: MTN ARCH test

F-statistics	2.604340	Prob. F (1.2494)	0.1067
Obs*R-squared	2.603710	Prob. Chi-Square (1)	0.1066

Source: Eview output using IRESS SA (2019)

Table C8: Heteroskedasticity Test: NPN ARCH test

F-statistics	62.21769	Prob. F (1.2494)	0.0000
Obs*R-squared	60.75200	Prob. Chi-Square (1)	0.0000

Source: Eview output using IRESS SA (2019)

Table C9: Heteroskedasticity Test: SHP ARCH test

F-statistics	41.64816	Prob. F (1.2494)	0.0000
Obs*R-squared	40.99694	Prob. Chi-Square (1)	0.0000

Source: Eview output using IRESS SA (2019)

Table C10: Heteroskedasticity Test: SOL ARCH test

F-statistics	41.64816	Prob. F (1.2494)	0.0000
Obs*R-squared	40.99694	Prob. Chi-Square (1)	0.0000

Source: Eview output using IRESS SA (2019)