FIRM SIZE AND THE DAY OF THE WEEK EFFECT ON THE JOHANNESBURG STOCK EXCHANGE

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DECLARATION

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DEDICATION

To my Parents and son (Willard Junior Chirunga), I owe you all the time I spent away from you.

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Above all, “And whatever you do, whether in word or deed, do it all in the name of the Lord Jesus, giving thanks to God the Father through him” (Colossians 3:17, *Holy Bible*, New International Version).

GLOSSARY OF ACRONYMS

AIC	- Akaike information criterion
AMH	- Adaptive Market Hypothesis
DOW	- Day of the Week
DSE	- Dhaka Stock Exchange
EMH	- Efficient Market Hypothesis
GARCH	- Generalized Autoregressive Conditional Heteroskedasticity
JSE	- Johannesburg Stock Exchange
LB	- Ljung Box
LM	- Lagrangian Multiplier
NSE	- National Stock Exchange
NYSE	- New York Stock Exchange
OLS	- Ordinary Least Squares
SIC	- Schwarz information criterion
U.S.	- United States
UK	- United Kingdom
USA	- United States of America
ZSE	- Zimbabwe Stock Exchange

ABSTRACT

The Efficient Market Hypothesis (EMH) asserts that stock prices always entirely reflect all available information and that stock prices follow a random walk, where future stock prices are not predictable based on historical prices (implying stock market efficiency). If the stock market is not efficient, abnormal returns can be realised by beating the stock market through observing and trading on certain patterns (anomalies) exhibited by past stock prices. Various anomalies have been documented, including the Day of the Week (DOW) effect (the tendency of a stock market to exhibit on average low daily returns in the beginning of the week (mostly on Mondays) and high returns towards the end of the week (mostly on Fridays). Examining the DOW effect is particularly interesting, as it demonstrates daily patterns on which investors can take advantage of this anomaly to realise excess returns on daily basis. One of the reasons that has been put forward as to what initiates the DOW effect, is measurement error as when a variable of interest either explanatory or dependent variable has some measurement error independent of its value. Thereby, leading to the notion that the DOW effect is present in medium and small markets or firms with low merchantability (firm size effect). However, from the South African literature, still has a gap about the existence of the DOW effect across firm sizes on the JSE and its cyclical (appearing or disappearing) changes over time.

Firstly, the study examined the existence of the DOW effect on the JSE in firm sizes on a full sample (1995 to 2019) utilising daily log-returns. The best-fit models were selected from a family of GARCH models, EGARCH (2, 1) and EGARCH (3, 1) models better fitted the AltX and the large index respectively and TGARCH (3, 1) and TGARCH (1, 1) better fitted medium and small indices respectively. The results showed that the DOW effect exists on the JSE stock exchange in three out of all the four investigated indices (medium, small and AltX except the large), particularly the DOW effect existed more in returns than in the volatility of those returns. Secondly, a rolling window analysis was utilised to examine the changes of the DOW effect over 1995- 2019 where the best-fit model for each sub-period was utilised. The results showed that the existence of the DOW effect is not constant over time concluding a cyclical behaviour (appearing and disappearing in some sub-periods). However, the highest frequency of appearance of the DOW effect appeared in the medium, small and the AltX indices confirming the notion that the DOW anomaly is mostly found in companies with low capitalisation.

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CHAPTER 1 : INTRODUCTION

1.1 Background of the Study

Investors generally desire high returns and low risk on their investments; however, they do not know in advance, what return their investments will generate, or what unseen risks the investment will face. One critical stage of the investment decision process involves an investment analysis, which is done by researching stock fundamentals and considering the potential impact and influence of domestic and global economic conditions, especially as they pertain to stock market (and stock price) behaviour (Avci, 2016). Among the reasons for this analysis, include an attempt to understand the nature of the investment in as much detail as possible, and having a good understanding of the projected returns and risks being investigated.

In a similar vein, understanding the market itself is essential. The efficiency of a stock market entails the extent to which the decisions of all the market contestants cumulatively reflect the value of listed companies and their share prices at any given time. The Efficient Market Hypothesis (EMH) of Fama (1965) asserts that stock prices always entirely reflect the available information and that stock prices follow a random walk, where future stock prices are not foreseeable based on past prices. Anwar and Mulyadi (2009) explained that a stock market is said to be inefficient when the current prices do not reflect all the publicly and privately available demand and supply information due to slackness or breakdown of buyer and seller communications. If the stock market is not efficient, abnormal returns will be realised by beating the stock market through observing and trading on certain patterns exhibited by past stock prices. Being able to earn abnormal profits by following return patterns is in contradiction to the EMH, where Fama (1965) argued that information contained in past prices is instantaneously fully reflected in current prices in an efficient stock market.

Contradictions to the EMH are commonly referred to as stock market anomalies. Poshakwale (1996) well defined the term *anomaly* as a circumstance that is not the same as the norm or the normal state. In the economic context of this study, an anomaly refers to the distortions in returns that contradict the EMH. Anwar and Mulyadi (2009) explained some seasonality or patterns in the stock returns that have been documented, including the turn of the month effect (a temporary increase in stock prices during the first few days and the last few days of each month). Other seasonalities include the Day of the Week (DOW) effect or Monday effect (the tendency of a stock market to exhibit on average low daily returns in the beginning of the week (mostly on Mondays) and high returns towards the end of the week (mostly on Fridays). Lastly, the Holiday effect (the tendency of a stock market to gain on the final trading day before an exchange-mandated long weekend or holiday such as Labor Day or Christmas holiday). Al-Loughani and Chappell (2001) pointed out that these anomalies collectively indicate that the expected return on a financial asset is not uniformly distributed across different units of time.

While several documented anomalies exist, DOW is particularly interesting as Barberis, Shleifer and Vishny (1998) explained that the DOW effect tends to show more performance and opportunities for investors to realise excess stock returns daily. Understanding the nature of the DOW is of great importance to the 'buy low, sell high' investors who can buy stocks on the day(s) in which the stock market yields low returns and sell on the day(s) in which yields high returns, thus maximising their abnormal profits on a daily basis. The interest in the DOW effect within the academic spheres started by French (1980) who documented negative returns on Mondays and favourable returns on other days of the week. Subsequent research by Gibbons and Hess (1981) verified the existence of this effect and found that its magnitude was large in small market capitalisation stocks.

Developing from this focus on returns, earlier studies on the DOW looked at the returns only. However, recent empirical studies are now considering not only the mean returns but also the volatility of stock returns. This recent consideration is found in the studies carried out by Dicle and Levendis (2014), Chia (2014), Akhter, Sandhu and Butt (2015) and Hasan (2017). In addition, the DOW effect in the volatility of returns has the support of Winkelried and Iberico (2015), who pointed out those risk-averse investors, would reduce their investment on those assets that are likely to increase in volatility at certain times. Therefore, Hasan (2017) put forward that consideration of both returns and volatility are critical to investors and added that investigating patterns in volatility is beneficial in several ways. These include the use of forecasted volatility patterns for hedging and speculative purposes, and in the valuation of certain assets such as stock index options.

Hassan (2013) explained that early investigations of the DOW effect had been predominantly concentrated on stock markets in developed countries and less on developing countries because the developed countries are assumed efficient. However, a conclusion has not been made yet on the existence of the DOW effect in emerging economies due to conflicting results. Ndako

(2013) and Saeed (2017) supports that many studies on the DOW effect are concentrated on stock markets in developed countries, mainly due to the higher degree of transparency of stock exchange institutions in developed markets that are assumed to be efficient and consequently the greater availability of appropriate data. There has seen an increased amount of research in the developed countries that are outside the African continent, while African stock markets, including South Africa, have received comparatively little attention.

The Johannesburg Stock Exchange (JSE) is a relatively the most liquid emerging market in Africa. The efficiency of the emerging markets assumes greater importance as the trend of investments is accelerating in these markets because of regulatory reforms and the removal of other barriers for international equity investments. This importance motivates finance researchers to study the existence of calendar anomalies or seasonality in stock returns and their volatility in the South African stock market.

According to Obalade and Muzindutsi (2019), JSE is ranked 19th largest stock exchange in the worldwide by capitalisation and it is the largest in the African continent. The South African stock market was founded on November 8, 1887, and is one of the largest exchanges in Africa by market capitalisation. As of 2019, it had a market capitalisation of $987 Billion, with 388 companies listed, 76 foreign domiciled companies and the ratio of market capitalisation over Gross Domestic Product of 278.94 per cent as put forward by Segun *et al.*, (2019). The discovery of gold in Witwatersrand in 1886 led to many mining and financial companies started calling the need to open a stock exchange. The JSE was formed during the first South Africa gold rush following first legislation considering the financial markets in 1947. The JSE joined the World Federation of Exchanges in 1963 and then advanced to electronic trading in 1995. The JSE plays one of the key roles in the economy, to provide a fair platform for companied and individual investors to access capital from willing investors. The stock exchange also allows a market place where securities can trade freely under a legislative board.

The empirical literature has shown that the existence of the DOW effect on the JSE has shown inconsistent results, and so it has not yet been conclusively demonstrated on how this particular anomaly presents in this market. These contradictory results were documented from similar study periods as well as related models and still yielded different results. The following are the most quoted DOW studies from the South African literature that show the developments in the use of different models from those which used descriptive statistics and Ordinary Least Squares

(OLS) focusing on the stock returns only. On the other hand, the volatility models were based on the Generalised Autoregressive Conditional Heteroskedasticity model (GARCH) and its extensions.

Njanike (2010) examined the Large –cap index on the JSE from 1995 to 2009 using the OLS regression model and found the DOW effect having only significant negative returns on Mondays. For the period from 1995 to 2010, Chinzara and Slyper (2010) studied if the DOW effect existed in the daily returns and volatility of four JSE sectors (Industrials, General Retailers, Mining and Financials). They found significant positive returns early in the week and significantly negative returns later in the week.

Similarly, Mbululu and Chipeta (2012) focused on indices returns of nine listed sectors (Oil & Gas, Basic Materials, Industrials, Consumer Goods, Health Care, Consumer Services, Telecom, Financials, Technology) to examine the existence of the DOW effect anomaly in the daily returns from 1995 to 2011. They recognised a Monday effect in the Basic Materials sector only. Plimsoll *et al.* (2013) did a microanalysis by investigating the existence of the DOW effect on the JSE Top 40's individual companies' returns and volatility from 1995 to 2012. The results showed that only ten of the Top 40 companies on the JSE showed significant pattern on at least one day of the week while no significant pattern was found on the volatility of the returns. These conflicting results led to the ambiguity about the existence of the DOW effect on the JSE, its nature, and how it can be applied in investment decisions. Therefore, despite the number of publications devoted to the DOW effect in South Africa, questions remain concerning the DOW effect in the South African stock market and include: (1) does the DOW effect anomaly differ across firm size and, (2) how does the anomaly change over time?

1.2 The Differences in Existing Empirical Findings

Lo (2004) stated that stock markets evolve from an inefficient to an efficient state (implies linear); hence, the DOW effect could disappear and re-appear (linear) in some periods, thereby following the Adaptive Market Hypothesis (AMH). The AMH implies that the key to survival is innovation, meaning that, as the risk or reward relationship varies, the better way of achieving a consistent level of expected returns is to adapt to the changing market conditions. Knowing whether the DOW effect exists as well as the nature of its changes over time is an essential consideration in developing markets which are regarded as emerging markets that are unlikely to be as efficient (or at least not efficient as much of the time) as developed markets. These inefficient stock markets are known to be affected by highly developed markets. Understanding the change in the DOW effect over time may offer valuable insight into periods where the DOW effect is or is not found. Hence, this study aims to contribute to the empirical literature by exploring the stock market returns and volatility in an attempt to understand the dynamics in the changes of the DOW effect over time, and across the different firm sizes.

1.2.1 The Research Problem

While the DOW effect has been studied extensively in developed countries, less attention has been given to this matter in developing countries, especially in Africa. The South African literature shows that the DOW effect has been examined in individual companies, sectorial and All-Share indices. The results around these studies are inconclusive and do not consider the DOW effects across firm size. Anwar and Mulyadi (2009) put forward that one possible reason that may explain the range of results in the same market is that detail is being lost in the aggregation of entire sectors. Specifically, Anwar and Mulyadi (2009) argued that the DOW effect is more likely to be seen in smaller firms.

While it has been noted that the DOW effect phenomenon in South Africa has been studied at an individual company or sector level, for the Top 40 companies on the JSE (which are large firms). There is still a gap in the South African literature to find out if this anomaly exists on the JSE according to company sizes (large, medium and small). The hypothesis is that smaller, less well-known firms are not likely to have the same information richness as larger firms, increasing the chance that smaller firms will demonstrate this anomaly. This study has also widened the research area by including the AltX index, which is an alternative public equity exchange for small and medium-sized companies in South Africa operating parallel with, and wholly-owned by, the JSE Securities Exchange. The inclusion of the AltX index in this study adds a new dimension of understanding in the South African literature with a focus on examining the hypothesis that the DOW effect is more likely to occur in smaller firms.

Lastly, the DOW effect has been examined in the South African Stock market in different areas such as individual companies and the stock indices grouped in sectors. The focus was only to determine the existence of the DOW effect in the stock market, and little is known on the changes of the DOW effect over time (years). In Australia and New Zealand (Chia (2014)), the

DOW effect was revisited by taking into account its presence in different periods but also could not factor in it is the changes over time. Although a few international studies (including Haroon and Shah (2013) and Rossi (2007)) have considered the DOW effect over time, little is known on the empirical evidence from the South African stock market context over time. Hence, this study examines if there are any noticeable changes over time about the DOW effect within the South African stock market while considering firm sizes by using the Large, Medium, Small and AltX indices.

The JSE large index includes the Top 40 on the local market companies with a market capitalisation of over R10 billion. The medium cap index comprises of stocks ranked from 41 to 100 on the market with a market capitalisation between R1 billion and R10 billion on the market. Small index represent companies with values less than the top 100 listed companies with market capitalisation of less than R1 billion (JSE website).

1.2.2 Research Objectives and Questions

The objectives of this study are to:

1. Determine if there exist significant evidence of the DOW effect in the indices'returns and their volatility differ across company sizes on the JSE, (using extensions of the GARCH model).
2. Examine any evidence of significant changes of the DOW effect over time, (by employing a rolling window approach) in returns and volatility across firm size on the JSE.

The research questions are as follows:

1. Is there evidence of the Day of the Week Effect in the Large-cap, Medium-cap, the Small-cap indices' and AltX index returns and their volatility of returns on the JSE?
2. How has the DOW effect changed from 1995 to 2019 across company sizes on the JSE?

1.3 Significance of the Study

The study offers a better understanding of market efficiency, specifically in terms of information efficiency, as evidenced by the presence or lack thereof of the DOW effect. Knowledge of this study can then be used by market participants, especially those interested in the timing aspects of the trade, and those seeking to utilise profit-making opportunities. Portfolio managers implement strategies that enable them to earn an abnormal profit based on the nature of the

DOW effect. The recent view that DOW effect can be exploited mostly small and not well-known companies is also of interest to investors as that may permit them to create suitable investment strategies. To add on, portfolio managers and investors who rely on volatility estimates in risk management and dynamic hedging strategies draw value from understanding changes or patterns of the DOW effect over time. Urquhart and McGroarty (2014) stated that investment strategies might be profitable for some time, but then disappear. That is, different investment strategies are successful in some periods, and unsuccessful in other periods in line with the Adaptive Market Hypothesis (AMH). Hence, the findings of this study allow investors to consider the potential of taking advantage of any predictable patterns of the DOW effect in designing the trading strategies. The understanding of the existence of the DOW effect in company sizes and trends over time is also of paramount importance to policymakers as that may help them in implementing policies that promote stock market efficiency by preventing the realisation of abnormal profits.

1.4 Structure of the Study

The layout of the dissertation contains six chapters. Chapter 1 offers a background to the research problem and provides a justification for the need to analyse the market returns in the South African environment. Chapter 2 is the theoretical foundation of the DOW effect and related phenomena. Chapter 3 is a detailed review of the empirical literature surrounding the DOW effect and is sub-divided into three sections. That is the evidence from the South African stock market, other African countries and the developed stock markets from different continents. Chapter 4 describes the dataset, together with an outline of how the returns were calculated and econometric methods used for data analysis. Section 5 discusses the results produced from each of the stages of the analytical techniques applied. Chapter 6 is the summary of the findings, limitations of the study, recommendations for further research and conclusions.

CHAPTER 2 : THEORETICAL FRAMEWORK

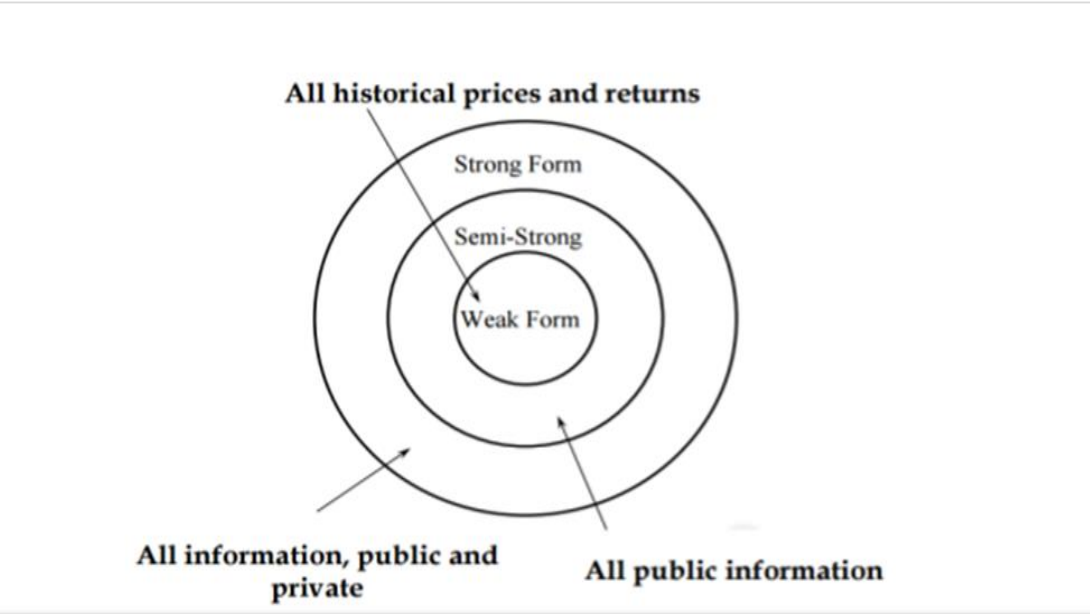
2.1 Introduction

This chapter covers the conceptual understanding of various explanations as to the existence of the DOW effect. The theoretical reasons as to why anomalies arise are also explained in the context of arbitrage limitations. The presence of anomalies leads to known return series behaviours such as volatility clustering and autocorrelation in financial data. This type of data may be examined with a family of GARCH models that are explained in detail below.

2.2 The EMH and the Random Walk Theory

According to Fama (1965), market efficiency is categorised into three levels depending on the type of information contained in market prices, namely: weak form, semi-strong and strong-form market efficiency (Figure 2-1). The weak form assumes that stock prices reflect all historic information about prices, trading volumes or short interest. The semi-strong version asserts that stock prices contain all publicly available information about the prospects of the company. Finally, the strong form states that stock prices contain all the information of any kind, including private (insider information) such that no one can beat the market.

Figure 2-1: Forms of Information-based Market Efficiency



Source: Fama (1965)

According to the EMH, prices of financial assets should fully reflect all the public and private information available to everybody in the market so that no investor earns abnormal profits.

Thus, stock prices at any given point in time are not biased in reflecting all the available information in the stock market. This lets investors to earn risk-adjusted returns as prices instantaneously respond to the new information. Saeed (2017) also added that the more the stock prices reflect all the information and respond correctly to new information, the more efficient will be the stock market in allocating investments in their investment baskets. This leads to the theory of random walk, which points out that prices do not follow any patterns, such that future movements cannot be forecasted.

Rich (2018) explained that all the information is incorporated in prices, which are independent and unpredictable. Moreover, the market has no *memory* of the price changes and movement, and thus such movements are random (Fama, 1970). Lean, Mishra and Smyth (2014) mentioned that many studies had utilized the random walk model to assess whether opportunities exist for earning abnormal returns from arbitrage. The random walk hypothesis has strong connections to the EMH, where investors cannot outperform the market when prices conform to the random walk theory. In the same view, the study done by Njanike (2010), exhibited that sometimes stock market prices move from their actual values, and these deviations can be completely random and uncorrelated. That is, prices are expected to change because of the arrival of new information that is also unpredictable. Therefore, the EMH proposes that it is not possible to outperform the market due to the market timing or selection of stocks.

In the economic environment, however, this is not always found to be the case, as different types of anomalies and seasonal components have been uncovered showing that the EMH does not hold all the time. Avci (2016) explained that sometimes stock markets fail to be efficient as per the assumptions of the EMH because when investors come together in public markets to price securities, suffer from biases that create excess volatility and market inefficiencies. Some investors tend to overreact or under-react, herd and focus on the short term returns. These circumstances are psychological biases that cause the market to respond and update itself incorrectly.

2.3 Violation of EMH Assumptions

Bodie (2010) explained that there had been much arguments about the EMH, and in some cases, it has been recognised that market engagements can go against the expectations of the EMH. The nonconformity of the EMH assumptions with stock markets operations, an anomaly will be known to be existing. A market anomaly is defined as a systematic pattern in an asset's return, which is unknown. Since this pattern is frequent, it implies that investors can take advantage of it, as there is some predictableness to it. Examples of market anomalies, which seem to predict superior returns, arise from factors such as a stock's price-earnings ratio. Basu (1983) established the phenomenon that a market anomaly is the one, which is commonly analysed and known as the size effect, as first documented by Banz (1981). The size effect is indicative of small capitalisation companies were on average, earn higher expected returns than their larger counterparts do.

Researchers such Brown, Keim, Kleidon and Marsh (1983), Roll (1983), Blume and Stambaugh (1983) and Rozeff and Kinney Jr (1976) recognised a similar market anomaly which occurs in the first two weeks of January and known as the small-firm-in January effect. This deals with movements in stock prices in a given period. Additionally, Arbel, Carvell and Strebel (1983) explained that the January effect in small firms is closely related to the neglected-firm effect, which refers to small firms being neglected by large institutional investors since the information on small firms is not easily accessible. This makes the small firms riskier and more likely to reward investors with higher expected returns.

2.4 Stock Market Anomalies

A market anomaly is a price action that contradicts the expected behaviour of the stock market. Some financial irregularities appear only once and disappear, but others appear consistently throughout the historical chart analysis. Traders and investors can use these unusual market behaviours to find opportunities throughout the stock market and earn excess returns. Anomalies do not only appear in indices but also stock options, stock futures and other investment classes. This study focuses on examining the nature of the DOW effect, and therefore, the theoretical literature is centered on this anomaly. Gibbons and Hess (1981) also found the existence of the DOW effect in T-bills and, whereas Roll (1984) supported that DOW effect has also been observed in orange juice futures. Yadav and Pope (1992) found the DOW effect in bonds where it was concluded that the longer the maturity of the bonds, the lower the Monday's returns. Further, Berument and Kiymaz (2003) found the DOW effect in the foreign exchange rate market.

Since the introduction of the EMH, a wide range of research studies have been devoted to the exploration of the efficiency of financial markets with numerous types of calendar anomalies prevalent in equity markets being globally highlighted by scholars. Floros and Salvador (2014) explained that typical period related anomalies relate to days of the week or months of the year exhibiting anomalous returns, most notably the January effect and the Monday effect. Evidence of seasonal anomalies violates the assumption of weak market efficiency, whereby market participants may be able to generate consistent excess returns. One could expect these exploitative effects to disappear over time, allowing only a short period in which to benefit from abnormal returns due to the assumption of the existence of rational arbitrageurs participating within the market.

The existence of abnormal returns are said to be inconsistent with predictions of efficient markets and rational expectations is inconsistent with asset pricing theory (Mahakud and Dash, 2016). This would imply a degree of predictability and be widely known and exploitable by market participants. One parallel notion is that levels of efficiency may vary over time based on the market situation. That is, they are a function of the volatility over some time, with calendar effects tending to be more positive in low volatility regimes and negative in higher volatility regimes (Floros and Salvador, 2014). In this vein, it seems prudent to be cognisant of, and provide for the different market situations based on periods with fluctuations in volatility regime.

2.5 Day of the Week Anomaly

The primary assumption behind the DOW effect is that market participant's exhibit behaviour that affects financial market returns on certain days of the week (Berument and Dogan, 2012). The most dominant name in the literature about the DOW effect is the commonly known Monday effect or weekend effect, which suggests that Mondays exhibit relatively lower returns when compared to other days of the week, with Fridays showing abnormally higher returns (Zhang, Lai, and Lin, 2017). The prevalence of this effect is of particular interest to scholars due to the two days of no trading over the weekend. Rational investors would price in the extra two days in the carry of money value, into the Friday share price. That is, the delayed time between the share purchase and settlement thereof means that shares purchased on a Friday would only settle on the next Monday, and the share price on Friday would be inclusive of the extra two days of interest before the settlement date (Kumar and Lee, 2016). Other theoretical explanations have been put forward to explain the existence of the DOW effect such as the trading activities of investors, investors' psychology and measurement error.

2.5.1 Trading Activities of Investors

One of the most examined and identified explanations for the negative returns on Monday, is the trading activities of investors. This explanation has to do with the Information Processing Hypothesis (IPH), which postulates that, during the week, investors may not have plenty of time to search for information. Thus, they purchase the stocks that their stockbrokers suggest for them. Stockbrokers' suggestions tend to keep step with the market's promptitude. According to Lewellen *et al.* (1979), 77% of 6 000 stockbrokers' recommendations suggests purchases, while only 23% suggest sales on a Friday. However, during the weekend, investors have the time to search for information and to organise their investment strategy.

Another research by Michaely, Rubin and Vedrashko (2016) shows that, on a given Friday, market participants may be pre-occupied with the upcoming weekend and therefore market reactions to firm specific announcements, such as earnings announcements, other corporate news events and merger announcements made on Fridays, are subdued, with a more reactive correction-taking place on Monday. This supports the findings of Yuan (2015) who shows that higher attention paid by investors, especially when market indices are high, leads to abnormal selling behaviours, which would be the case on a Monday following a relatively negative announcement on Friday.

2.5.2 Investors' Psychology

Avci (2016) put forward that many analysts support that investors' psychology can play a significant role in causing the DOW effect phenomenon. More specifically, most investors regard Monday as the worst day of the week for the reason that it is the first working day of the week and Friday is considered the best day because it is the last working day of the week. Hence, investors feel pessimistically on Monday and hopefully on Fridays resulting in low returns on Mondays and high returns on Friday as found by Winkelried and Iberico (2015).

2.5.3 Measurement Error

The measurement error also contributes to the existence of the DOW effect. Onoh and Ndu-Okereke (2016) defined measurement error as when a variable of interest either explanatory or dependent variable has some measurement error independent of its value. It also added that there are many times that measurement error is considered to be the cause of the DOW effect phenomenon, mostly because this phenomenon appears to be stronger for companies with low capitalisation. Akhter *et al.* (2015) also explained that the measurement error arises from stocks that have low merchantability in those companies with small capitalisation and concluded that this error could bring positive effects in Friday's prices and negative effects in Monday's prices. For this reason, this study aims to examine this assertion in the South African stock market.

2.6 Limits to Arbitrage

The EMH acknowledges that mispricing of stocks is found in the stock market, but Shleifer and Vishny (1997) explained that investors could not realise excess or abnormal returns due to the concept of the limits to arbitrage that delays the flow of wealth from irrational to sophisticated investors. In practice, arbitraging involves taking advantage of a price difference between in separate stock markets by simultaneously buying and selling an asset, and in the process, the arbitrageur pockets a risk-free return. The following reasons explain how arbitraging or earning of abnormal returns is limited when stocks are mispriced.

2.6.1 Fundamental and Noise Trader Risk

Arbitrageurs may identify a mispriced security that does not have a close substitute for enabling a riskless arbitrage. If a piece of bad news affects the substitute security involved in hedging, the arbitrageur may be subject to unanticipated losses. Noise traders limit arbitrage, and once a position is taken, noise traders may drive prices farther from fundamental value, and the arbitrageur may be forced to invest additional capital, which may not be available, forcing an early liquidation of the position. Shleifer and Vishny (1997) pointed out that many do not have access to the same information that professional, specialised arbitrageurs do. These professional arbitrageurs, who thus do the bulk of the market's arbitrage work, will go out and raise capital from third parties to ply their trade. If an arbitrage spread widens, third parties may disrupt the arbitrage process by pulling their wealth just when it is most needed to keep an arbitrage trade on.

2.6.2 Implementation Costs

Kumar and Lee (2016) pointed out that short selling is often used in the arbitrage process, although it can be expensive due to the *short rebate*, representing the costs to borrow the stock to be instantly sold. In some cases, such borrowing costs may exceed potential profits. If short rebate fees are 10% or 20%, then arbitrage profits must exceed these costs to achieve profitability.

2.6.3 Performance Requirements/Agency Costs

Another short-circuits to the arbitrage process relates to limits imposed by variations in performance, and how they affect money manager incentives. They consider the pressures produced by tracking error, or the tendency of returns to deviate from a benchmark. It is therefore interesting to examine if the DOW effect exists regardless of these limits to arbitrage. This means that as markets respond to the new information with small or large price movements (volatility), makes some price series behaviour resulting in the concept of volatility clustering.

2.7 Adaptive Market Hypothesis (AMH)

After all the above-mentioned reasons attributed to the limitation of investors to earn abnormal returns, recent empirical evidence suggests that the DOW effect still exists in the stock markets. However, some argue that the existence of this anomaly is not persistent. Lo (2004) postulated that people are not completely rational actors as assumed by many economic and the EMH assumptions. Further, added that investor behaviours such as loss aversion, overconfidence, and overreaction are consistent with evolutionary models of human behaviour, which include actions such as competition, adaptation and natural selection. The AMH combines principles of the well-known and often controversial EMH with the principles of behavioural finance.

The AMH can be viewed as a new version of the EMH, derived from evolutionary principles, where prices reflect as much information as dictated by the combination of environmental conditions, the number and nature of *species* in the economy. The AMH has several implications that differentiate it from the EMH to the extent that the existence of the relationship between risk and reward is considered unlikely to be stable over time. This relation is influenced by the relative sizes and preferences of populations and by institutional aspects. As these factors change, any risk and reward relationship is likely to change as well. The hypothesis assumes that there are opportunities for arbitrage (Obalade and Muzindutsi, 2019). This implies that investment strategies, including quantitatively, fundamentally and technically based methods, perform well in specific environments and poorly in others. As such, the primary objective becomes survival with profit and utility maximisation being secondary. When a multiplicity of capabilities that work under different environmental conditions evolves, investment managers are less prone to become extinct after rapid changes. Therefore, the key to survival is innovation, where the variation in the risk/reward relation is associated with a better way of achieving a consistent level of expected returns by adapting to the changing market conditions.

2.8 The Relationship between the EMH, AMH and the DOW Effect

The debate around EMH has caused much controversy with the field of behavioural finance opposing the major assumptions of EMH. The EMH assumes that stock markets are always efficient and investors or traders cannot earn abnormal returns; however, this is not always as the case as different types of anomalies are found in various markets particularly the DOW effect. At times, it is difficult to reach a common ground with both these financial theories. Therefore, the field of AMH introduces a new approach to financial markets, which is significantly influenced by the developments in the discipline of evolutionary psychology by Farmer and Lo (1999), Farmer (2002). This stipulates that market participants evolve, compete and adapt to changing market conditions. Wilson (1975) applied the principles of reproduction, competition and natural selection to social interactions that were found to explain fascinating human behaviour. For example, how people select their partners, morality, ethics, altruism, kin selection and language, could be used in the context of finance and economics. This enables EMH and behavioural finance to reconcile.

The AMH is a new theory aimed at reconciling EMH and behavioural finance. It is viewed as a new version of EMH, which incorporates psychological biases. EMH is a combination of market conditions, number of participants, market size and the ability of security prices to reflect information instantaneously (Neely and Weller, 2013). The theory of AMH suggests that market participants are dependent on economic profits for their survival for market interactions and financial innovation to be derived readily. This implies that in a large market where resources and prices of securities are readily available, there are a large number of investors competing for those stocks. Therefore, this market tends to be more efficient as investors compete for these stocks, adapt to market conditions and bring prices of shares back to their intrinsic value Lo (2004).

In contrast, behavioural finance suggests that psychologists apply a heuristic to finance before reconciling EMH and behavioural. As a result, participants are be affected by different changes such as markets undergoing profits and losses due to changing market conditions, opportunities that exist, as new participants enter and exit the market, and shifting of opportunities. Behaviourists believe that the downfall of rational thinking is caused by greed and fear and that the ability to adapt improves the chances of achieving average returns (Lo, 2004).

Considering the ever-changing market conditions, the need for the knowledge of the change of the DOW effect over time becomes inevitable. Therefore, it is crucial to understand the nature of the DOW effect and the changes over time so that different strategies can be applied to fit the prevailing market conditions. This brings the nature of stock returns where one needs to check for the presents of the volatility clustering, persistence and autocorrelation as it is assumed that the change of stock prices (where stock returns are calculated from) are random and uncorrelated.

Seetharam (2016) have tested the AMH with a focus on providing a framework for testing the dynamic (cyclical) notion of market efficiency using South African equity data (44 shares and 6 indices) over the period 1997 to 2014. Firstly, it was explained that, the examination of market efficiency depending on a single frequency of data, might give conflicting conclusions. Second, if the data was divided into smaller sub-samples, one can obtain a pattern of whether the equity market is efficient or not. In other words, one might get a conclusion of, say, randomness, over the entire sample period of daily data, but there may be pockets of non-randomness with the daily data.

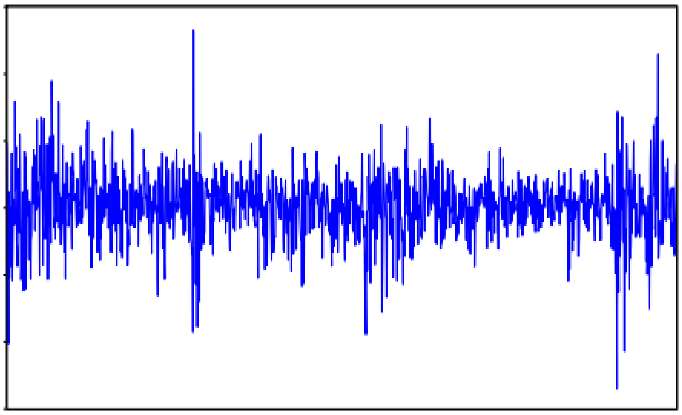
Third, by running a variety of tests, one provides robustness to the results. This is a somewhat debateable issue as one could either run a variety of tests (each being an improvement over the other) or argue the theoretical merits of each test before selecting the more appropriate one. Fourth, analysis according to industries also adds to the result of efficiency, if markets have high concentration sectors (such as the JSE), one might be tempted to conclude that the entire JSE exhibits, say, randomness, where it could be driven by the resources sector as opposed to any other sector.

Lastly, the use of neural networks as approximates is of benefit when examining data with less than ideal sample sizes. (Seetharam, 2016) Five frequencies of data were examined; 86% of the shares and indices exhibited a random walk under daily data, 78% under weekly data, 56% under monthly data, 22% under quarterly data and 24% under semi-annual data. The results over the entire sample period and non-overlapping sub-samples showed that this model's accuracy varied over time. Coupled with the results of the trading strategies, one can conclude that the nature of market efficiency in South Africa can be seen as time dependent, in line with the implication of the AMH.

2.9 Volatility Clustering and Autocorrelation

Volatility clustering is observed when stock prices exhibit high and low volatility in different periods. In other words, if massive price changes occur and persist for some time, the result is clustering. Volatility clustering has also been described as, “large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes”, Mandelbrot (1963;432) and is illustrated in Figure 2.2.

Figure 2-2: An Example of Volatility Clustering of Share Returns



Source: Eviews

The family of ARCH models that are detailed in Chapter 4 can explain the volatility clustering and autocorrelation. We utilised the extension of GARCH models in our analysis to correct the linear model and accurately explain the volatility clustering. Simple regression features advocate that the observed data should have a fixed mean and standard deviation. Also, the time series should be stationary and without any autocorrelations. Any violations of the regression standards result in an invalid model. In such cases, a more suitable model becomes necessary. This study followed the approach of testing for the autocorrelation in the data and conducting normality tests. As the EMH assumes that the fluctuations of stock prices are caused by the readily available information and are instantaneous following the random walk theory, therefore the volatility patterns are assumed not to be systematic. If the DOW effect exists in the volatility of stock returns, it implies that the EMH does not hold and investors can take advantage of the systematic behavior (DOW effect) and earn abnormal returns.

After Engle *et al.* (1987) noticed high autocorrelation in squared returns and suggested an ARCH model that allows a way to model the change in variance in a time series. Linking with second objective of this study to examine change of the DOW effect in volatility of returns (variance). Therefore, this study selected the ARCH models to account for the changes in volatility of log-returns of the selected indices. Bollerslev *et al.* (1994) suggested the GARCH model, an extension of the ARCH model that also incorporates a moving average factor. The introduction of the moving average factor enables the GARCH model to consider both change in variance as well as changes in time-dependant variance (Primsoll *et al*, 2013). The main advantage of the GARCH model is that it has much less parameters and performs better than the ARCH model.

A study by Zivot (2008) explained the difference between the ARCH and GARCH models where it was put forward that the GARCH model has only three parameters that allow for an infinite number of squared roots to influence the conditional variance. This characteristic enables GARCH to be more parsimonious than ARCH model. In brief, GARCH is a better fit for modelling time series data when the data exhibits heteroskedasticity and volatility clustering. However, in some cases there are aspects of the model that can be improved so that it can better detect the features and dynamics of a particular time series. For example, a standard GARCH model fails in capturing the "leverage effects" which are observed in the financial time series. In other words, based on this model, good and bad news have the same effect on the volatility. Therefore, to address this problem, several GARCH models extensions were proposed but the mostly used ones in the DOW effect literature were discussed in chapter 4.

The DOW effect literature have considered the basic GARCH model and the following extensions; EGARCH, TGARCH and GARCH in Mean models as they examine the combination of stock returns and their volatility. The equations and details of each of the GARCH models are disussed in detail in the methodology section (chapter 4). To achieve the objectives of this study, the GARCH (p, q) and its extensions were fitted and the model diagnostics were used to select the best model fit. Dicle and Levendis (2014), Mazviona and Ndlovu (2016), argued that the basic GARCH model come with some shortcomings of not accounting for leverage effects. The leverage effects being the generally negative correlation between an asset return and its changes of volatility and that of not allowing feedback between the conditional variance and the conditional mean. However, in some instances the GARCH model is found to be the best fitting model so it was also used for statistical inferences together with its extended models in order to have robust and more informed statistical results.

Previous studies, Berument and Kiymaz (2001), Rahman (2009), Akhter *et al.* (2015), Choudhry (2000) applied the basic GARCH model to account for the volatility aspect in examining the DOW effect. However, the current study follows the studies conducted by Chinzara and Slyper (2010) and Osarumwense (2015) which spoke to the short comings of the basic GARCH model by using its extended models (the Exponential Generalised Autoregressive

Conditional Heteroskedasticity (EGARCH), the GARCH in Mean and the TGARCH models). They applied these extensions in examining the existence of the DOW effect because they all cover the limitations of the basic GARCH model. This study harnessed the strengths of both the basic GARCH model and its extensions in order to maximise the amount of information captured by the models in explaining DOW patterns in the JSE daily stock returns.

2.10 Time-varying of the DOW effect

EMH continues to bring controversies as investors' advances their trading patterns in trying to maximise their average returns as well as improving in their stock selections. Other theories have begun to challenge the EMH assumptions and are considering a more suitable framework for the explanation of the stock return behaviour. Lo (2004) advocated for the AMH theory which supports the exploration of the time-varying efficiency in stock markets using the analogy from market dynamics, interactions and innovation. AMH suggested a new way of analyising stock market anomalies, which is to examine the pattern of stock returns over time.

Therefore, the second objective of the study is to test change of the DOW effect across firm size. In the context of AMH, can the DOW effect change over time? Little is known in the South African literature about the time-varying change of the DOW effect. Obalade and Muzinditsi (2019) explained that the consideration of time –varying DOW effect is new and the investigation is still limited to developed countries. Studies which which have supported the time-varying behaviour include, Osamah and Ali (2017) and Shanke *et al* (2013) on pre- and post- financial crisis using the rolling window estimation. Further, Obalade and Muzindutsi (2018) show that African stock markets has time-varying DOW effect. Therefore, the current study will make meaningful contribution to the validation of the AMH in South African stock market context.

2.11 Chapter Summary

Overall, the existence of the DOW effect appears to arise from the mismatch of the EMH assumptions with the actual level of efficiency of a number of stock markets. The limits to arbitrage tend to avoid the realisation of abnormal returns due to transactional costs and noise traders, leading the stock market to go back to its efficient state. The DOW effect appears to still be existing in number stock markets and found to be more common in small firms than large firms. The existence of the DOW effect has been attributed to measurement error, trading activities of investors and investors' psychology. Different investing strategies are supposed to relate to different market conditions as supported by the AMH. Therefore, the evidence that the DOW effect exists in small firms and its changes are scanty in the context of the South African stock market. In that way, this study is motivated to examine such existence of the DOW effect across different firm sizes and its change over time in order to promote adaptive investment strategies to earn abnormal returns.

CHAPTER 3 : EMPIRICAL EVIDENCE

3.1 Introduction

This review focused specifically on the DOW effect that is in line with the objectives of the study. Studies of the DOW effect have largely been conducted in developed stock markets outside the African continent, with fewer studies in developing stock markets, such as South Africa. Studies that have been examined the existence of the DOW effect in the South African stock market have tended to show conflicting results as to whether this effect is present or not. The following sections discuss the empirical evidence on the DOW effect from the South African stock market, followed by those documented in other countries on the African continent, and lastly, studies conducted in international countries.

3.2 South African Empirical Studies

Bhana (1985) conducted one of the earliest studies on the presence of the DOW effect on the JSE. Upon examination of the shares of the companies traded on JSE between 1978 and 1983 using multiple regression, the results found out that Monday trading sessions experienced the most adverse average returns, whilst Wednesday sessions producing the most positive returns. The investigated DOW effects were based on individual companies' perspective. Chang *et al.* (1993) included South Africa in their sample spanning from 1985 to 1992 for the JSE All Share index data and applied the OLS model to examine the existence of the DOW effect at a market level. They found the evidence of a DOW effect only in France, Italy, the Netherlands, Spain and Sweden. These countries' results differed in the specific day that the effect was present.

From an industrial or sectorial perspective, Coutts and Sheikh (2002) examined the existence of the DOW effect in the Gold index on the JSE from 1987 to 1997, using the OLS model as well. The study found no evidence of the DOW effect. Hence, it makes sense that these early studies investigated the DOW effect in stock returns but did not consider the corresponding volatility of the returns, prompting this study also consider the volatility aspect.

Alagidede (2008) included the South African stock market in examining the presence of the DOW effect in both stock returns and volatility at a market level. Several other countries were also considered, including: Egypt, Kenya, Morocco and Tunisia; Zimbabwe, and Nigeria. Data were obtained from various years in which each of the selected countries' stock exchanges started trading, for the period beginning the year 1995 up to 2006. The statistical models used were OLS, ARCH and GARCH. The results showed that no DOW effect was found in Egypt, Kenya, Morocco and Tunisia. A positive Friday effect was evident in Zimbabwe and Nigeria whilst negative Friday effect in South Africa. These results differed from the expected nature of the DOW effect where negative returns are found at the beginning of the week (Monday and Tuesday).

On the other hand, Chinzara and Slyper (2010) collected data from Thompson DataStream. These data consisted of daily closing prices for a 16-year period starting 1 January 30 1995 to 31st December 2010 for the All Share Index and four other indices which represented the more prominent sectors of the JSE. The four sectors chosen were the FTSE/JSE indices of Industrials (IND), General Retailers (RET), Mining (MIN) and Financials (FIN). Their findings indicated that the daily returns seem to have exhibited significant positive returns early in the week and significantly negative returns later in the week for both the All Share Index and the sector indices. Although Alagidede (2008) and Chinzara and Slyper (2010) applied a similar methodology of the general GARCH (1.1) model, Chinzara and Slyper argued that this approach does not fully address the characteristics of volatility in that the asymmetric information is not captured. The asymmetric information is where there is imperfect knowledge, which is believed to be captured by the GARCH, TGARCH and EGARCH models.

Mbululu and Chipeta (2012) focused on a similar area of study by examining the existence of the DOW effect in the stock market sectors on the JSE from 3 July 1995 to 13 May 2011. They tested the DOW effect using descriptive statistics and focusing on the skewness and kurtosis of nine-listed stock market sector indices' returns namely: Oil & Gas (J500), Basic Materials (J510), Industrials (J520), Consumer Goods (J530), Health Care (J540), Consumer Services (J550), Telecom (J560), Financials (J580), and Technology (J590). However, these did not consider volatility. The empirical results of their study showed no evidence of the DOW effect on skewness and kurtosis for eight of the nine JSE stock market sectors, Only the Monday effect was detected for the basic materials sector.

Darrat, Li and Chung (2013) investigated the existence of the DOW effect in the South African stock market from 1973 to 2012 using the GARCH model whilst considering both the returns and volatility. The data used were obtained from the JSE All Share Index (ALSI). They found a negative Monday effect that disappeared in 2008 and still with no indication of how the DOW effect changed over time. This brings about the realisation of the gap in the time-change factor component on the DOW effect and consequently attracting the need for the application of the rolling window approach that is explained in detail in the methodology section.

On the contrary, Plimsoll *et al.* (2013) explored the existence of the DOW effect on the returns and volatility on the JSE, focusing on determining the existence of the DOW effect on individual companies on the market's Top 40 firms and the All Share Index. This study by Plimsoll *et al.* (2013) appears to be the most 'micro' investigation of the DOW effect conducted to date in the South African stock market. By regressing returns on each day of the week separately with the TGARCH estimation model, they showed that the ALSI, in aggregate had no any significant DOW effect. However, on a firm-specific level, 10 of the Top40 firms had significant DOW effect on at least one day of the week. The investigation revealed no significant DOW effects concerning volatility.

Atsin and Ocran (2015) investigated the existence of calendar effects and market anomalies on the JSE using monthly and daily closing prices of the ALSI, Top 40, Mid Cap and Small Cap index as well as daily closing prices on the Value, Growth and Dividend Plus indices during the period from 2002 to 2013. The anomalies analysed were the January effect, the weekend effect, the size effect, the value effect, and the dividend yield effect. The empirical analysis used a number of Markov Switching Autoregressive models with a different number of regimes and lag orders. The results from the investigation showed the non-existence of the January effect and the value effect on the JSE during the periods 2002 – 2013 and 2004 – 2013, respectively. However, evidence of the weekend effect was found in the Mid Cap and the Small Cap indices. The size effect was also found to be statistically significant during the same period 2002 - 2013.

Most recently, Rich (2018) investigated the DOW effect focusing on the firm size on the large cap index, medium cap index and small cap index from 2002 to December 2017. The study focused on the stock index returns only, using the Makorv Switch Model allowing temporary probabilities to vary between different scenarios (best and worst cases). The results showed no significant DOW effect and did not consider the volatility of returns or the changes of the DOW effect over time. This strengthens the main motivation of this current study to discover the nature of DOW effect on the stock returns and their volatility as well as their change over time. In addition, this current study aims to examine the large, medium, small and AltX indices, using the more established methodological approach of the GARCH family based on data from 1995 to 2019. This expands on Rich (2018)'s sample by adding more than a full year of data. Literature has shown that the GARCH model was last used in 2013, which is more than a decade ago from the time of this study. During that period, Rich (2018) did not consider the GARCH because the attention was given to the examination of the returns only. By also including, the AltX index to this current research adds knowledge to the context of the South African stock markets where there is limited information about the DOW effect. More so, another view angle to be considered is the continuous change of the DOW effect over time regardless of the scenarios.

Generally, it is clear from the South African related literature on stock markets that there still exists indecision about any fixed or sure presence of the DOW effect on the JSE stock market. The studies on the DOW effect in South Africa have examined the returns and their volatility in different areas. Chinzara and Slyper (2010) focused on the JSE sector indices using the basic GARCH model and its extensions. Mbululu and Chipeta (2012) examined the same area but focusing on the returns only using the descriptive statistics. Plimsoll, Saban, Spheris, and Rajaratnam (2013) focused on examining the existence of the DOW effect in individual companies. Bhana (1985), Chinzara and Slyper (2010) and Darrat et al. (2013) detected the DOW effect, although it was spurious and inconsistent, where the contradictory results may be attributed to different statistical methods implemented. On the other hand, where the firm size effect had been incorporated as in the case of Rich (2018), only the stock returns were considered and without the application of the GARCH model. In general, these studies were performed over various periods and using different statistical techniques. There was a lack of consistency in the methodology and findings, triggering the need for exploring the DOW effect with a different focus to establish whether the occurrence indeed exists, and if does so, then determine the possibility of change over time.

3.3 African Empirical Studies

Discussed in this section are the few studies that were conducted outside South Africa but within the boundaries of the African continent. They are discussed according to the model developments from the use the OLS approach focusing on the stock returns only, followed by those other studies which included volatility in their investigations of the DOW effect.

Osarumwense (2015) assessed the influence of error distributional assumption on the appearance or disappearance of the DOW effects in the returns and volatility using the Nigerian stock exchange (NSE-30). The study comprehensively assessed three main error distributional assumptions for the DOW effect in the returns and their volatility, for the period of four years (31 May 2011 to 2 May 2015). The GARCH (2, 1) and EAGRCH (2, 1) models were used to capture the volatility clustering effect as well as the leverage effects. However, the evidence presented in this study reveals that the DOW effect in the Nigerian stock exchange (NSE-30) on the returns and volatility was sensitive to the distributional assumptions. These findings showed that the DOW effect anomaly varied depending on the assumption made on the returns and variance. In other words, the idea of DOW effect in the Nigerian stock market was not real due to the error distributional assumption influencing the appearance or disappearance of calendar effects. The results revealed that the DOW effect was sensitive to error distribution where the good or bad news in volatility did not only depend on the asymmetric model but also the choice of the error distribution. Thus, the study would provide adequate knowledge to policy makers, investors and researchers about DOW in stock markets.

In the same Nigerian Stock Market, Onoh and Ndu- Okereke (2016) documented that the stock returns varied with the day of the week in both the developed stock markets and in the emerging stock markets. The study hence, examined the presence of the DOW effect in the All Share Index of Nigerian Stock Exchange. The OLS model was used to analyse the stock returns pattern for a period ranging from the 2nd of January 2009 to the 31st of December 2015. The results gotten from the study revealed that Friday returns were significantly higher than the returns of the other days of the week. The outcomes confirmed the existence of the day of the week effect in the NSE daily returns.

On the other hand, Mazviona and Ndlovu (2016) examined the DOW effect on the Zimbabwe Stock Exchange (ZSE). The objective of the study was to relate the overall stock market returns to the individual returns trading days (Monday, Tuesday, Wednesday, Thursday and Friday). The objective was to find whether returns of trading days were statistically different from each other. The OLS model was also used to model the returns. The study focused on ZSE stocks with data from 19 February 2009 when the ZSE started to trade in United States dollars up to 31 December 2013 examining Sixty-two stocks. Stocks contained by the Industrial and Mining index were utilised in the modelling application. The data was obtained from the ZSE website and other secondary data sources such as journal articles, papers and reports. The study found

found slight presence of day of the week effect, with about 26% of the stocks having significant positive and negative returns. Eventually they concluded that the mean returns of the stocks on the ZSE under their study period did not differ across the trading days at the 5% level of significance.

In general, the results reported in the previous studies within the boundaries of the African continent were similar in terms of the study area. They focused on the existence of the DOW effect using similar models, the area of study and mostly examining the DOW effect on returns only not considering volatility of returns as well. The results have shown that DOW effect exists in some stock markets but found in other stock markets. Therefore, the knowledge about the DOW effect remains not conclusive and this study goes further in unpacking its existence across firm size. Moreover, these previous studies have also shown the gap in the literature about the changes of the DOW effect in the African continent

3.4 International Empirical Studies

The international empirical evidence is unpacked according to the development of the models applied including the OLS and, where only the returns were considered in examining the existence of the DOW effect. This is followed by studies which included volatility and consequently the incorporation of volatility models (the basic GARCH model and its extensions). Cai *et al.* (2006) studied the DOW effect for A shares and B shares traded on the Shanghai and Shenzhen stock exchanges in China. The study period was from 1992 to 2002 using the OLS model and they found that the average Monday returns from A-share indexes were significantly negative during the third and fourth weeks, similar to the U.S. market. However, the average Tuesday returns on most of the A-shares and B-shares indices were negative during the second week of the month. Even after controlling for autocorrelation and the spill over impact from regional and international markets, the DOW effect in the Chinese market remained significant.

Similarly, Benjamin and Bin (2010) endeavoured to study the DOW effect in the top 50 Australian companies across different industrial sectors. Their study looked at the weekday seasonality using stock return data of individual companies. Utilising the daily data for the period of January 2001 through to June 2010, they provided descriptive statistics of the returns. The results showed that the weekday anomalies were mixed across the companies and industries. Further, they found that the largest mean weekday returns occurred on Monday among the 15 of the companies, most of which were the materials and energy companies. In addition, the study indicated that the returns on Monday were significantly larger than the other four days for six companies and results differ from the expected DOW effect where there are low returns at the beginning of the week and high returns at the end of the week.

The following studies used the OLS and the results were conflicting too. Saeed (2017) conducted a study to analyse the day of the week effect in three emerging markets namely, Pakistan on KSE100, India on BSESN and Malaysia on KLCI in the period of 2008-2012. The data was collected from Yahoo Finance. The descriptive statistics were performed to find the general trends of data using the OLS that indicated that there were no anomalies in the behaviour of the returns in these emerging markets. Avci (2016) studied the existence of the DOW effect on the pre (before) and post (after) subprime crisis periods, in terms of the conventional or Islamic of indexes for Canada, Indonesia, Japan, UK and USA markets during the period of 2003-2014 and using the OLS method too. The findings of the study showed significant DOW effect for all the indexes involved, though such effect was not persistent. When the DOW effect was examined in terms of the conventional and Islamic indexes of each market, there was no persistent conformity on the DOW effect for both indexes of the same markets.

The following studies are among the ones increasing in the recent years and superior to the older and inconsistent methods in examining the DOW effect such as the descriptive statistics and OLS. The GARCH models are superior in the sense that they produce results that include both the stock returns and their volatility in the examination of the DOW effect. The most quoted and popular study was conducted by Kiymaz and Berument (2003) in investigating the DOW effect on the volatility of major stock market indexes for the period of 1988 through to 2002 where a conditional variance framework from the GARCH (1.1) model was used. The data consisted of the daily prices of TSE-Composite (Canada), DAX (Germany), Nikkei-225 (Japan), FT-100 (UK), and NYSE-Composite (NYSE). The results showed that the DOW effect was present in both the returns and the volatility equations. The highest volatility occurred on Mondays for Germany and Japan, on Fridays for Canada and the United States, and on Thursdays for the United Kingdom. The study supported the argument that high volatility would be accompanied by low trading volume because of the unwillingness of liquidity traders to trade in periods of high stock market volatility.

Rahman (2009) also studied the presence of the DOW effect anomaly in Dhaka Stock Exchange (DSE) during a study period from 2005 to 2008. The study used both dummy variable

OLS regression model and the GARCH (1, 1). The results indicated that Sunday and Monday returns were significantly negative and the positive returns were on Thursdays only. The results also revealed that the mean daily returns between two consecutive days, Monday to Tuesday differed significantly for the pairs, Wednesday-Thursday and Thursday-Sunday. Further, it was shown that the average daily returns of every working day of the week was significantly different. The dummy variable regression results showed that only Thursdays had positive and statistically significant coefficients. The results of the GARCH (1, 1) model showed statistically significant negative coefficients for Sunday and Monday and statistically significant positive coefficient for Thursday dummies. The findings from this study revealed that there was a significant DOW effect in the DSE.

In supporting the existence of the DOW effect using the GARCH model, Winkelried and Iberico (2015) conducted a study to check the existence of significant and robustness of the DOW effects in the main Latin America from 1995 to 2014. Upon performing the analysis, estimates from the GARCH (1, 1) model, exhibited a negative Monday effect and a positive Friday effect also showing an evidence of the turn of the Month effect.

The GARCH (1, 1) received some criticisms of not accounting for leverage effects. Generally, the leverage effects are a negative correlation between an asset return and its changes of volatility. This does not allow the feedback between the conditional variance and the conditional mean. The following studies found the presence of the DOW effect after employing the extensions of the GARCH model. Dicle and Levendis (2014) determined whether the DOW effect was still existing, and evaluated empirically the explanations of the DOW effect for international equity markets. The study evaluated 51 markets in 33 countries for the period between January 2000 and December 2007 using the DJR-GARCH (1, 1) model. The results revealed that the DOW effect persisted for a significant proportion of equity markets.

To add on, Chia (2014) examined the existence of the daily pattern of calendar anomalies and asymmetrical behaviour in Australia and New Zealand stock markets over the period 2002 to 2014. The study found disappearing DOW effect in the returns of both the Australian and New Zealand stock markets. By using the TAR-GARCH (1, 1) model, the study uncovered that there appeared to be an asymmetrical market reaction to the positive and negative news in both of the stock markets. It was believed that the consistence of these findings has useful implications for trading strategies and investment decisions. Thus, investors should use the information to avoid and reduce the risk when investing in these markets.

3.5 Summary of the Empirical Evidence

It appears that the DOW effect in stock returns and volatility is still a topical subject as the results differed across countries, time, and the applied methodology. Some studies were conducted at micro-level, which is, looking at individual firms, while others were conducted at macro-level, looking at the entire stock markets (sector indices). As such, there is a similar gap in the understanding of the DOW effect in the South African context. While this topic has been documented in the literature, the findings are mixed; therefore, it is interesting and relevant to examine the case of the South African stock market. In summary, the DOW effects have been studied in individual companies, the sectorial indices and the JSE All Share. However, from the reviewed empirical evidence, it can be realised that less attention has been given to the examination of the DOW effect anomaly across the firm sizes and changes of the DOW effect over the years.

In addition, the empirical literature evidence has shown that the recent studies on both the returns and volatility were conducted mostly in the developed countries. When considering the volatility aspect, the GARCH (1, 1) found to have some shortcomings of not considering the leverage and asymmetric effects which helps in explaining the nature of the pattern of the volatility. The extension of the GARCH model (EGARCH, TGARCH and GARCH in Mean) were later introduced to counter for such limitations of the basic GARCH model. However, the discussed literature lacks the empirical evidence pertaining the changes of the DOW effect over time. Hence, the interest of this study is to uncover the longitudinal effect using an updated approach of the rolling window to incorporate the volatility aspect and consequently enhancing the limited empirical literature, particularly in the context of the South African stock markets. Table 3.1 summarises the key developments in the evolutionary understanding of the DOW.

Table 3-1: Summary of Empirical Literature

Country and Authors	Period	Method	Results
South Africa			
Bhana (1985).	1978-1983	OLS	Negative Monday; positive Wednesday
Chang *et al*. (1993),	1985-1992	OLS	Negative Monday and Positive Friday
Coutts and Sheikh (2002)	1987-1997	OLS	No DOW Effect.
Alagidede (2008)	1995-2000	OLS, ARCH and GARCH	Negative Monday, Tuesday and Friday
Chinzara and Slyper (2010)	1995- 2010	GARCH, TGARCH and EGARCH	Negative Monday and Positive Friday; Lower volatility on Monday, higher on Friday; overall DOW effect in volatility
Mbululu and Chipeta (2012)	1995- 2011	skewness and kurtosis	No DOW Effect
Darrat *et al*. (2013)	1973- 2012	GARCH and rolling window approach	Negative Monday and No indication of DOW effect changing over time.
Plimsoll *et al.* (2013)	1995- 2012	TGARCH	No DOW Effect in returns and in volatility
Atsin and Ocran (2015)	2002- 2013	Makorv Switch model	No DOW effect and the size effect was present
Rich (2018)	2002 -2017	Markov Switch model	No DOW effect in returns
Nigeria			
Osarumwense (2015)	2011-2015	GARCH and EAGRCH	DOW is present but varies with different distribution made.
Onoh and Ndu- Okereke (2016)	2009 -2015	OLS	Positive Friday effect
Zimbabwe			
Mazviona and Ndlovu (2016)	2009-2013	OLS	Slight DOW effect
China			
Cai *et al.* (2006)	1992-2002	OLS	Negative Monday and Tuesday
Australia			
Benjamin and Bin (2010)	2001- 2010	OLS	Positive Monday
Chia (2014)	2002- 2014	TAR-GARCH	An asymmetrical market reaction to the positive and negative news
Pakistan			
Saeed (2017)	2003-2012	OLS	No DOW effect
USA			
Avci (2016)	2003-2014	OLS	No DOW effect
Kiymaz and Berument (2003)	1988 -2002	GARCH	DOW effect was found in both returns and volatility
Winkelried and Iberico (2015)	1995- 2014	GARCH	Negative Monday effect and a positive Friday effect
Dicle and Levendis (2014)	2000- 2007	DJR-GARCH	DOW was present, Positive Friday
Bangladesh			

Rahman (2009)	2005- 2008	GARCH	Significant negative coefficients for Sunday and Monday and positive Thursday effect

Source: Authors Own Compilation

CHAPTER 4 : DATA AND RESEARCH METHODOLOGY

4.1 The Data

This study used secondary data that was collected from the Bloomberg database. It consists of daily closing prices of four indices, namely: the Large-Cap index (J200), Mid Cap index (J201), Small-Cap index (J202) and the AltX index (J233). In line with Rich (2018), Winkelried and Iberico (2015), Mbululu and Chipeta (2012) and Chinzara and Slyper (2010), the study period was from 1995 to 2019. It is noted, however, that the availability of data for the medium and small indices started in 2002 and 2006 respectively as those were the years in which they were introduced. This implies that there were four data sets (one for each index) with closing dates that are the same, with different starting dates (only the large index starts from 1995). The full length of the large index data set is 5 943 observations of daily returns. The other indices had 4 314 (medium index), 4 313 (small index), and 3 249 (AltX index) observations.

Daily returns were used to test for the DOW effect, which were calculated as the continuously compounded daily closing prices of each index converted into natural logarithms (Brooks (2014). This approach follows Chinzara and Slyper (2010)'s methodology, as shown in Equation 1.

$$R_t = \ln(P_t/P_{t-1}) * 100 \quad \text{...} (1)$$

Where:

t = present day,

R_t= continuously compounded returns on day t

P_t = stock index price on day t,

P_{t-1}= stock index in previous day t-1

ln = Natural logarithm operator

Following Mei-ting (2012) and others, Monday return was calculated as log $(\frac{Closing\ price\ on\ Monday}{Closing\ price\ on\ Firday}) * 100$.

The data preparation and calculation of daily returns was done in a Statistical Computing Software R, version 3.5.3. This includes the formulation of dummies for the DOW effect analysis, and extracting the data for each window for the rolling window analysis. The stationarity plots were also visualised using R. All the R codes were provided in Appendix 1.

The data set price series exhibited some discontinuities, mainly on holidays. To solve the effect of missing observations due to non-trading days, linear interpolation was implemented. This approach was used because Chitzitzisi (2017) suggested that this method facilitates the subsequent procedure of rolling regression, where the sample rolls 5 days at a time meaning the length of a week. The linear interpolation method is a linear approximation of the missing value calculated as a combination of the previous non-missing value and the next non-missing value: IV_{Linear} = (1-ʎ)P_{i-1} + ʎP_{i+1}

Where:

IV_{Linear} = interpolated value

ʎ = is the weight coefficient which essentially is the relative position of the missing value divided by the total number of missing values in row

P_{i-1} = the previous non-missing value

P_{i+1} = the next non-missing value.

An example of this method, for a single NA value, the interpolated value will be halfway the distance between the two prices, and the terminology will be shown as ʎ = ½. For two NAs in a row the first value interpolated will be interpolated as 1/3, while the second value will be interpolated 2/3 of the same distance between the previous and the next non-missing value computed with ʎ = 2/3. This method would deliver a 5-day sample for each week excluding weekend where the stock market was closed.

For example

Before	After
0.0907	0.0907
NA	0.0588
0.0269	0.0269

This method has an advantage of keeping the same mean and the same sample size (Hawthorne and Elliot, 2005). Data preparation, creation of dummy variables and estimation of ARIMA structures were done in R software, while all the preliminary tests and the econometric models (GARCH models) were done in Eviews software.

4.2 Dummy Variables

Wissmann and Toutenburg (2011) defined a dummy as a variable that takes the values 0 or 1 only, and these two values do not have to bear a specific quantitative meaning. Dummies were used to classify non - mutually exclusive categories and can be called indicator variables. In this study the DOW effect (which is examined on five days - Monday through to Friday) was indicated by the values of 0 or 1. That is, if the day of the week is said to be Monday it takes the value of 1 and 0 otherwise (the 0 corresponding to Tuesday to Friday). To check Monday, Monday get a value of 1 and the rest of the days of the trading week are assigned a 0, and the same goes on until the 5^{th} day of the week (Friday). In other words, the values represent the presence or absence of the categorical value.

When using dummy variables, one must be aware of the problem of the dummy variable trap. McGahan and Mitchell (2003) defined the dummy variable trap as a scenario in which the independent variables are multi-collinear (where two or more variables are highly correlated). In simple terms, where one variable can be predicted from the others. Balestra (1990) explained that, given an equation or a model with dummy variables, this problem can be solved by dropping one of the categorical variables, or alternatively, dropping the intercept constant. If there are *m* number of categories, then *m-1* of them are used in the model. The value left out can be thought of as the reference value and the fit values of the remaining categories represent the change from this reference. In this study, *m* was 5, implying five dummy variables representing Monday, Tuesday, Wednesday, Thursday and Friday.

Yip and Tsang (2007) pointed out that dummy variables can be used in seasonal analysis and went on to explain that there are two ways of entering dummy variables into regressions in such seasonal analysis to avoid the dummy trap and the associated interpretations. The first, and less often used, approach is to include the full set of dummy variables with, say, *j* mutually exclusive and exhaustive dummy variables and exclude the constant term. This approach effectively partitions the seasonal effect in question or being examined on the dependent variable for the *j* categories (which are the dummies representing the days of the week). As a result, this approach of handling dummy variables is called the partition approach.

The second, and more often used approach, is to include the main effect or the dependant variable and *j – 1* dummy variables. This would mean that the dropped-out category or dummy variable is chosen as the base, with which the other categories are compared – this method is called the base approach.

The study by Yip and Tsang (2007) went on prove that both approaches give the same coefficient estimates. They also give the same R^2 and other statistics, such as log-likelihood and F-statistic. The only difference concerns the interpretation of the relational and seasonal effect terms. Gujarati (2004) interpreted that, if the regression contains a constant term, the number of dummy variables must be one less than the number of classifications of each qualitative variable. Implying that the coefficient attached to the dummy variables must always be interpreted in relation to the base, in this case – the reference day of the week receives the value of zero. The base or the reference day chosen would depend on the purpose of research at hand, for example if the research were examining the positive Friday effect only the Friday would be the base or the reference day.

Gujarati (2004) also explains that the second approach of omitting the constant or the intercept term results in assigning a dummy variable to each category be it quarter, month of the year or day of the week. If there is any seasonal effect in a given quarter, month or day of the week that will be indicated by a statistically significant t value of the dummy coefficient for that day of the week. Therefore, the method that was applicable to this study was the partition approach as explained by Gujarati (2004), Yip and Tsang (2007) of dropping the constant or the intercept in the regressions.

Therefore, the reason for selecting the partition approach is that the objective of this study is to examine if there is any evidence of the DOW effect in the Large-cap, Medium-cap, the Small-cap indices' and AltX index returns and their volatility of returns on the JSE implying that the partition method of omitting the intercept was applicable. The reason being that the objective of the study was not to focus or reference on a particular day (as assumed by the base approach of eliminating one of the dummy variables) but examining which day of all five days of the week indicate the seasonal effect, if any.

DOW effect studies used dummy variables to capture the categorical effect of each day of the week using either of the two approaches mentioned before to avoid the dummy trap. More specifically, the partition approach used in this study was also applied and is supported by its use in the following studies: Rossi (2007), Chinzara and Slyper (2010), also Osarumwense

(2015) who all used the coefficients the dummy variables for Monday, Tuesday, Wednesday, Thursday and Friday (dropping the constant). The dummy variable trap was avoided with the exclusion of the constant in the model also follows the studies of Berument and Kiymaz (2001), Chatzitzisi (2017) and Zhang, Lai and Lin (2016), amongst others.

Therefore, since the interest is to assess if the DOW effect exists in any day of the week and this study opted to solve the dummy variable trap by dropping the constant in the mean equation of each of the GARCH models in order to find the significance of each day of the week coefficients. However, due to mathematical formulation of the variance equation, the dummy trap cannot be solved by dropping the constant (Obalade and Muzindutsi, 2019). Therefore, the day of the week found least often to be statistically significant from the mean equation is excluded here, as no statistical inference would be concluded from an insignificant estimate.

4.3 The Research Methodology

This section outlines how the statistical methods were used after data preparation. Initially, the calculated indices' returns were tested for stationarity and the models used for stationarity were explained in detail. This chapter reviews main concepts of non-stationary time series and provides a description of some tests for time series stationarity. Hamilton (1994), Fuller (1996), Enders (2004), Harris (1995) and Verbeek (2008) explained that there are two principal methods of detecting non-stationarity: visual inspection of the time series graph and its correlogram and formal statistical tests of unit roots.

Followed by the finding the statistical structures of the stationary returns series in terms of an Autoregressive-Moving Average processes and checking for auto- relation and presence of ARCH effects in order to check if the nature of the returns meet the conditions to run the GARCH models. The best-fit model was chosen among the chosen (based on the GARCH models that were widely used in the DOW effect literature) extensions of the GARCH models using Information Criteria and model diagnostics (ARCH effects must be present). Finally, the results from the best-fit model were used to the research questions.

4.3.1 Initial Diagnostic Tests of the Data

Prior to testing for the presence of the day of the week effect, diagnostic tests on the data were performed to better understand the characteristics of the series and the implications thereof for their modelling in the study. This section contains the descriptive statistics, volatility clustering plots of returns and the stationary tests (unit root tests) both visual and formal tests. For this purpose, tests of stationarity, normality, autocorrelation and heteroscedasticity were performed, with the details of these tests briefly outlined below.

4.3.1.1 Testing for Stationarity

It has been widely documented that time series data tends to be non-stationary, implying that it may behave as a random walk process such that it deviates far from the long-term mean without reverting to the mean again (Lamba and Otchere, 2001). The use of non-stationary data yields a spurious relationship[1] with very high R-squared values (R^2) (Brooks, 2014). As such, a test for stationarity should be conducted before running a regression. A shock is usually used to describe an unexpected change in a variable or in the value of the error terms at a particular time. Having a stationary series, the effect of a shock will die out gradually. However, in a non-stationary system, the effect of a shock is permanent.

A non-stationary time series is called integrated if it can be transformed by first differencing once or a very few into a stationary process. The order of integration is the minimum number of times a series needs to be differenced to yield a stationary series. An integrated series of order 1 time is donated by I (1) while a stationary time series is said to be integrated at order zero, I (0). We have two types of non-stationarity. In an AR (1) model we have: Unit root: = 1: homogeneous non-stationarity and an explosive root: > 1: explosive non-stationarity. In an explosive case, a shock to the system become more influential as time goes on though it can never be seen in real life. This study will not consider it because share returns rarely show an explosive behaviour due to the natural logarithm operator which incorporated in their calculations.

The Augmented Dickey Fuller (ADF), the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) and the Philips Peron (PP) tests were used for this purpose in this study. The ADF is the benchmark test, while the other two are often used as supplementary tests to verify the ADF results. In our data series, all the three tests were used to conclude on the return series, thus to verify if the results are indeed robust.

[1] Brooks (2014) shows that the application of standard regression techniques to non-stationary data yields a regression with significant coefficient estimates and high R^2 but with no economic value.

The ADF test, developed by Dickey and Fuller (1979), is an autoregressive test that focuses on determining whether a shock to the series dissipates over time (as should be the case for a stationary process) or whether the effects remain in the system without dying away as is the case for a non-stationary variable. The specification of the test also includes lags of the dependent variable (the differenced series) as extra explanatory variables to soak up the effects of autocorrelation (Brooks, 2014). However, it is important to ascertain the optimal number of lags to include as using too many lags reduces the power of the test by consuming degrees of freedom.

For this purpose, information criteria such as Akaike's (1974) information criterion (*AIC*) and Schwarz's (1978) Bayesian information criterion (*SBIC*) are frequently employed. The E-Views automatic lag length selection based on SBIC was used for this purpose. The SBIC is consistent which results in the selection of the optimum number of lags in a large sample, whereas AIC is not consistent meaning that it fails to choose the correct number of lags with a high probability in large samples, such as that used in this study.

The test for non-stationarity was conducted with an intercept but without a trend in the test equation since the graphical plots showed no trend. Therefore, the ADF non-stationarity test was carried out by estimating the following regression:

$$\Delta y_t = \psi y_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta y_{t-i} + u_t \quad \text{.........................} (2)$$

y_t is a time series of daily index return data, p is the number of lags of the time series of daily index return and u_t is a white noise process (Brooks, 2014). If a series is non-stationary, then it is said to have a unit root. The null and alternative hypotheses for each series were:

$$H_0:\ y_t \sim I\ (1)\ (series\ has\ a\ unit\ root)$$
$$H_1:\ y_t \sim I\ (0)(series\ is\ stationary)$$

The rejection of the null hypothesis therefore implies that the series is stationary. A common drawback of the ADF test is that it fails to distinguish highly persistent but stationary processes from non-stationary processes (Brooks, 2014). Therefore, this study also performed the Phillips– Perron test by estimating the following equation;

$$y_t = \alpha + \rho y_{t-1} + \epsilon_i \quad \text{..........................} (3)$$

The PP tests correct for any serial correlation and heteroskedasticity in the errors u_t from equation (2) non-parametrically by modifying the Dickey Fuller test statistics. Phillips and Perron's test statistics can be viewed as Dickey–Fuller statistics that have been made robust to serial correlation by using the Newey–West (1987) heteroskedasticity and autocorrelation-consistent covariance matrix estimator. The null and alternative hypotheses for each series were:

$$H_0:\ y_t{\sim}I\ (1)\ (series\ has\ a\ unit\ root)$$
$$H_1:\ y_t{\sim}I\ (0)(series\ is\ stationary)$$

One advantage of the PP tests over the ADF tests is that the PP tests are robust to general forms of heteroskedasticity in the error term u_t. Another advantage is that the user does not have to specify a lag length for the test regression.

The KPSS test was also performed to solve the drawback of the ADF test that fails to distinguish highly persistent but stationary processes from non-stationary processes. Also, as a confirmatory analysis, which avoids this problem by testing whether a series is stationary around a deterministic trend rather than whether it is non-stationary as per the ADF test (Kwiatkowski *et al.*, 1992). More explicitly, the null and alternative hypothesis for each series y_t were:

$$H_0\ :\ y_t\ \sim\ I\ (0)\ (series\ is\ stationary)$$
$$H_1\ :\ y_t\ \sim\ I\ (1)(series\ has\ a\ unit\ root)$$

The E-Views automatic lag length selection was used and an intercept was included in the test equation similarly to the ADF test. On the other hand, theoretically, Davidson and MacKinnon, (2004) mentioned that in the case of different conclusions being reached, the KPSS can used since the ADF and PP tests tend to be biased towards the rejection of the null hypothesis when the series has a root close to the unit circle.

4.3.1.2 Test for Normality

Testing whether the residuals of a regression are normally distributed is a common diagnostic test as if the residuals do not meet this condition, then the standard hypothesis tests based on the *t*- and *F*-statistics only follow the *t*- and *F*-distributions asymptotically. Thus, in a small sample any hypothesis testing may be invalid (Brooks, 2014). However, in the context of assessing the properties of the return series, it is necessary to ascertain whether they are normally distributed because fat tails and a more peaked mean (the characteristics of a leptokurtic distribution) are commonly observed in series that exhibit time-varying volatility or volatility clustering. Thus, the rejection of a normally distributed series is a common characteristic of time-series data with heteroscedasticity and as such, is usually a common test performed on the data to assess whether volatility clustering may be present (Birău, 2011).

In financial time series data, the most widely used test for normality is the Jarque-Bera (JB) test by Jarque and Bera (1981). This statistic measures the difference in the skewness and kurtosis of a series with those of the normal distribution. A normal distribution should have zero skewness as it is symmetrical, while the measure of kurtosis, which captures how fat the tails and how peaky the mean of the distribution is, should be three for a normal distribution.

The JB test statistic is computed as:

$$\text{JB statistic} = \frac{N}{6}\ (S^2 + \frac{(K-3)^2}{4})$$

Where: S denotes the skewness and K the kurtosis (Brooks, 2014). This JB statistic is distributed as χ^2 with two degrees of freedom. The null and alternative hypotheses for this test are:

$$H_0\text{: } The\ returns\ are\ normally\ distributed$$
$$H_1\text{: } The\ returns\ are\ not\ normally\ distributed.$$

If the JB test statistic is statistically significant at the 5% level of significance then the null hypothesis was rejected in favour of the alternative hypothesis that the returns are not normally distributed (Brooks, 2014). If this is the case, then conclusions can be drawn as to whether the series follow a leptokurtic or platykurtic distribution by examining the measures of kurtosis while the values of skewness will indicate whether more positive or negative returns were obtained. From the empirical evidence, many DOW studies tested for normality in share returns (including the recent ones of Osarumwense (2015), Rupando (2015), and Rich (2018)) by applying Jarque-Bera (JB) test. Their results showed that their return series were found not to be normally distributed.

4.3.1.3 Tests for Serial Correlation

Similarly, to the test of normality, tests for autocorrelation in the residuals of a regression are frequently conducted because such patterns can give rise to inefficient standard errors and hence incorrect inferences from hypothesis tests (Brooks, 2014). However, in the context of examining share or index returns explicitly, autocorrelation tests provide information about correlation in returns across time and thus, as mentioned in chapter 3, may indicate the presence of the DOW effect in the market as they trade on past prices. For example, days of an increase in volatility is followed by increase in volatility and it is the same days of low volatility are followed by low volatility in the market. These changes in volatility will give rise to further increases or decreases in the share price thus leading to correlation between the share returns in the previous and current periods.

Although several authors, including Sentana and Wadhwani (1992), LeBaron, (1992) and Campbell, Lo and MacKinlay (1997) have demonstrated that autocorrelation patterns are more complex than this simplistic explanation provided here. Analysing the basic patterns of serial correlation in share returns is an important first step in analysing the properties of the series and whether the DOW effect may be evidenced on the JSE.

The Breusch-Godfrey test for autocorrelation, which is a more general test that is used to test higher order serial correlations under the null hypothesis of no serial correlation was used. This Lagrangian Multiplier (LM) test is more versatile than other tests such as the Durbin-Watson test, which is difficult to interpret (Brooks, 2008:148). The LM test statistic is computed as:

$$LM\ Statistic = (n - \rho) * R^2$$

where: n is the number of observations used to estimate equation 4.6, ρ is the number of lags of the residuals and R^2 is the coefficient of determination from this test regression (Brooks, 2008:149). The LM test statistic follows a χ_q^2 distribution and the null hypothesis is rejected if the test statistic is greater than the critical value. Therefore, if the test statistic was found to be significant at the 5% level of significance then it indicated the presence of serial correlation.

In addition to the Breusch-Godfrey test for autocorrelation, the Ljung-Box (LB) test was used to examine whether the returns exhibited significant serial correlation. For this test, it is necessary to specify the number of lags over which to examine patterns of autocorrelation. McQuarrie and Tsai (1998) argued that there is no universally agreed number of lags to be used for time series data. Bhatti, Al-Shanfari and Hossain (2006) showed that a long lag length eliminates autocorrelations in residuals, that is, the more lags used the greater the chance of identifying any autocorrelation. This study used daily data, which has the potential to be correlated over numerous periods and therefore, 36 lags (the maximum possible lags of 36 in E-Views) were used. It should be noted that the same number of lags were used for all tests that required a specified number of lags. The LB Q-statistic was computed as:

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

Where: T is the number of observations, τ_j is the j^{th} order autocorrelation and Q is asymptotically χ^2distributed with j degrees of freedom.

The null and alternative hypotheses for the LB test are:

$$H_0: The\ returns\ are\ not\ serially\ correlated$$
$$H_1: The\ returns\ are\ serially\ correlated.$$

If the Q-statistic from the LB test was found to be significant at the 5% significance level, then the null hypothesis that the returns were uncorrelated was rejected in favour of the alternative that there was evidence of a relationship between the current and past period returns. As mentioned, such a conclusion may be indicative of feedback trading.

4.3.1.4 Tests for ARCH Effects

To confirm the appropriateness of the GARCH specification for modelling the conditional volatility of the return series, two tests for ARCH effects were performed. A regression line was fitted to check for the presence of ARCH effects in the residuals of each return's series of the indices. The periods of low volatility are followed by periods of low volatility for a prolonged period. Again, the periods of high volatility are followed by periods of high volatility were shown in the visual displays, then there will be justification for running the ARCH models. To confirm these results, the fitted regression lines (3) on each of the indices' return series were used test the presence of the ARCH effects in the residuals. Therefore, in testing the presence of ARCH effects in the residuals of an estimated linear regression of log-return series against its lagged returns values.

Ndako (2013) explained that to test for ARCH effects in the conditional variance of u_t (σ_t^2 = Var ($u_t\ \Omega_{t-1}$)), where, Ω_{t-1} is the publicly available information at time t-1, two steps are followed: First, we consider the Auto-regressive of order 1, AR (1) model for the return's series of each individual index as in (2):

$$r_t = \beta_0 + \beta_1 r_{t-1} + u_t \text{.. (4),}$$

and run the linear regression on it to obtain the residuals u_t. Secondly, we run a regression of squared OLS residuals, (u_t^2) obtained from equation (3) on q lags of squared residuals to test for ARCH of order q. The ARCH (q) specification for σ_t^2 is denoted as:

$$\sigma_t^2 = \propto_0 + \propto_1 u_{t-1}^2 + \propto_2 u_{t-2}^2 + \cdots + \propto_q u_{t-q}^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

The null hypothesis states that there is no ARCH effect and is given by:

$$H_0 : \propto_1 = \propto_2 = \cdots = \propto_q = 0,$$

This is tested against the alternative hypothesis that the auto-correlations are not zeros, implying that there is an ARCH effect at the time lags.

$$H_0 = \propto_1 \neq 0, \propto_2 \neq 0, \ldots \propto_q \neq 0.$$

The first of these tests is the LB test described above, but instead of the test being conducted on the returns, the squared returns are used as an approximation of the volatility of the series. Thus, the identical test statistic was computed using the autocorrelation measures from the squared returns, with the hypotheses tested as follows:

$$H_0: The\ volatility\ of\ the\ returns\ is\ not\ serially\ correlated$$
$$H_1: The\ volatlity\ of\ the\ returns\ is\ serially\ correlated.$$

If this test statistic was greater than the critical value, then the null hypothesis of no autocorrelation in the squared returns was rejected in favour of the alternative that there was serial correlation in the volatility (Brooks, 2014). Evidence of serial correlation in the volatility not only indicates that there is evidence of volatility clustering (periods of high volatility follow periods of high volatility and periods of low volatility follow periods of low volatility) but also that volatility does vary over time and thus the series exhibits heteroscedasticity (Tsay, 2014).

The second test that was used to confirm the conclusions drawn from the LB test on the squared returns was Engle's (1982) ARCH test. The focus of this test is also to test for serial correlation in the volatility of the return series i.e. testing for volatility clustering (i.e. ARCH effects). The null and alternative hypotheses of this test are as follows:

$$H_0: There\ are\ no\ ARCH\ effects\ in\ the\ series$$
$$H_1: There\ are\ ARCH\ effects\ in\ the\ series$$

In order to test the null hypothesis of no ARCH up to order q, the following regression was run:

$$e_t^2 = \beta_0 + \left(\sum_{s=1}^{q} \beta_s e_{t-s}^2\right) + \upsilon_t \quad \ldots\ldots\ldots\ldots \quad (6)$$

Where: e is the residual from a regression of the series returns against a constant and q refers to the maximum number of lagged squared residuals (s) that are included (Brooks, 2014).

Engle's Lagrangian Multiplier (LM) test statistic is computed as:

$$LM\ statistic = n * R^2 \quad \ldots\ldots\ldots (7)$$

The LM test statistic follows a χ_q^2 distribution and the null hypothesis is rejected if the test statistic is greater than the critical value. Therefore, if the test statistic was found to be significant at the 5% level of significance, then there were ARCH effects in the return series meaning that the volatility varies over time and follows an autoregressive pattern; thus, warranting the use of a GARCH model (Brooks, 2014).

4.3.2 Estimation of the ARMA or ARIMA Processes

Hannan (1980) explained that an auto-regressive of order p, AR[2] (p) and a moving average of order q, MA[3] (q) move in opposite directions and can be combined to form an Autoregressive Moving Average (ARMA (p, q)) model. An Autoregressive-Moving Average (ARMA) or Autoregressive Integrated Moving Average (ARIMA) process be incorporated in the model to examine the behavioural nature of the stationary data or returns. According to Brooks (2014), if the return series is found to be stationary at level that is I (0) follows an ARMA process while a return series that attained stationarity through differencing follows an ARIMA process.

The characteristics of these models are summarised in Table 4-1;

Table 4-1: Summary of Characteristics of ACF and PACF

Model	ACF Pattern	PACF Pattern
AR (*p*)	Exponential decay or damped sine wave pattern or both	Significant spikes through first lag
MA (*q*)	Significant spikes through first lag	Exponential decay
ARMA (*1, 1*)	Exponential decay from lag 1	Exponential decay from lag 1
ARMA (*p, q*)	Exponential decay	Exponential decay

Source: Author's Own Compilation

[2] An **AR** (1) autoregressive **process** is the first-order **process**, meaning that the current value is based on the immediately preceding value, while an **AR** (2) **process** has the current value based on the previous two values. An **AR** (0) **process** is used for white noise and has no dependence between the terms.

[3] A succession of averages derived from successive segments (typically of constant size and overlapping) of a series of values.

An ARMA or ARIMA process is the basic model for analysing a stationary time series data. First, although the stationarity has to be defined formally in terms of the behaviour of the autocorrelation function (ACF), through Wold's decomposition. Every stationary data-generating process can be approximated by an ARMA or ARIMA (p, q) process where choice of the orders p and q of the process and estimation of all process parameters. The objective is to fit a stationary ARMA or ARIMA (p, q) process to a set of $t = 1\ldots$ T observations. An ARMA or ARIMA model can be estimated using the Box-Jenkins methodology in the following steps:

Step 1: **Identification** - involves looking at the line graph of the variable and also looking at its correlation function (ACF) as well as partial autocorrelation function (PACF) and check whether the log- returns series is following an AR or MA or ARMA model. Tentative models are identified which are going to be estimated in step 2 in order to find the best fit ARMA or ARIMA model.

Step 2: **Estimation** – Involves the estimation of least squares on all the combinations of ARMA or ARIMA (p, q) models regression based on the findings from the step 1 on the number of lags shown by the spikes and find out if the coefficients of AR (p) and MA (q) are significant. It is done by over fitting which involves deliberately fitting a larger model than that required to capture the dynamics of the data as identified in step 1.

Step 3: **Model Checking** – After estimating all the tentative models, the better model was selected basing upon having most significant coefficients of AR(p) and MA(q), lowest AIC and SIC and highest adjusted R^2.

Gujarati and Porter (2009) explained that the fundamental idea from the Box-Jenkins methodology is that of parsimony (meagreness or stinginess). Parsimonious models produce better results than over-parameterised models and the goodness of fit of the model improves with an increasing R^2 but such a model is penalised with a reducing adjusted R^2 which my tilt towards zero if there are too many irrelevant variables added to the model. Therefore, fitting an ARMA or ARIMA model to a data series is more of an “art than of science” Gujarati (2004:840). In this study, the best applicable model would be selected through step 2 and 3 thus estimation of the parsimonious models and select the best which pass the step 3 (model checking).

Zhang (2018) pointed out that Akaike’s information criterion (AIC) compares the quality of a set of statistical models to each other. For example, you might be interested in what variables contribute to low socioeconomic status and how the variables contribute to that status. Let us say, you create several regression models for various factors like education, family size, or disability status; the AIC will take each model and rank them from best to worst. The best model will be the one that neither under-fits nor over-fits.

Although the AIC will choose the best model from a set, it will not say anything about *absolute* quality. In other words, if all of your models are poor, it will choose the best of a bad bunch. Therefore, once you have selected the best model, consider running a hypothesis test to figure out the relationship between the variables in your model and the outcome of interest. The BIC is also known as the *Schwarz information criterion* (SIC) or the *Schwarz-Bayesian information criteria*. It was published in a 1978 paper by Gideon E. Schwarz, and is closely related to the Akaike information criterion (AIC) which was formally published in 1974.

4.3.3 Econometric Models

After testing the stationarity of the return's series of the indices, the study estimated GARCH family models and their extensions in order to select best model that could capture all the characteristics of the data (calculated LOG returns). The following four GARCH models are the widely used GARCH, TGARCH and EGARCH in the literature, Chinzara, Slyper (2010) Plimsoll *et al*. (2013) and Chia (2014) utilised the TGARCH model, and Dicle and Levendis (2014) applied the GARCH in Mean model. Referring to the literature concerning the examination of the nature of the DOW effect, (basic GARCH, T-GARCH, E-GARCH and GARCH in Mean). Brooks (2014) mentioned that the best model should be one that is able to capture all the data characteristics such as the ARCH effects and auto-correlation. The best model was selected by comparing the performances of the chosen GARCH models using the statistical information criteria (The Akaike information criterion (AIC), Schwarz information criterion (SIC) and Hannan-Quinn Information Criterion (HQIC).

Gayawan and Ipinyomi (2009) explained that the model with the lowest or minimum values of AIC, SIC and HQIC is considered to be the best model for statistical inference. When the information criteria results give conflicting results, Brooks (2014) pointed out that an AIC criterion is commonly used to select the best model. This was also supported by Chinzara and Slyper (2010) and Osarumwense (2015), pointing out their results that the selection of the best model gives more statistically robust results.

The first objective of the study was to determine if the DOW effect exists in the four chosen indices' (large-cap, medium, small-cap and AltX) returns and in volatility of their returns. Of interest was to assess whether these indices' returns statistically differ from each other on each day of the week not only focusing on the negative Monday effect and positive Friday effect as done by previous studies. If the DOW effect is *not* found to be present, it implies that the returns for each day of the week do not statistically differ from each other. Therefore, the p-values of the dummy variables should not be statistically significant, and *vice versa*. Each of the chosen models are explained in detail below.

GARCH (p, q) Model

This model was suggested by Engle *et al.* (1987) and is particularly one of the non-linear models that has proved very useful in the application to many economic time series, especially in the financial time series analysis. The model consists of two components, namely: a moving average of order (p) and the autocorrelation of order (q). Bollerslev *et al.* (1994) explained that p and q are usually referred to as time lags. The general form of a GARCH (p, q) model is defined as in (8).

$$\sigma_t^2 = \propto_0 + \propto_1 u_{t-1}^2 + \propto_2 u_{t-2}^2 + \cdots + \propto_q u_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_q \sigma_{t-q}^2 \text{.......} \quad (8)$$

Where:

p = the order of the moving average ARCH terms

q = the order of the autoregressive GARCH terms.

A generally accepted notation for an ARCH model is to specify the ARCH function with the q parameter ARCH (q); for example, ARCH (1) would be a first order ARCH model while the GARCH model is to specify the GARCH function with the p and q parameters, GARCH (p, q), say. For example, the GARCH (1, 1) would be a first order GARCH model. Therefore, the GARCH model subsumes ARCH models, where a GARCH (0, q) is equivalent to an ARCH (q) model. To estimate the model, the lagged ARCH and GARCH terms are both set to 1 (p = 1 and q = 1). The GARCH (1, 1) is the simplest and the most commonly used type of volatility models. It has a mean and variance equations given in the form of (9) and (10) respectively.

Mean Equation

This equation follows the standard OLS methodology by regressing the returns on five dummy variables as follows:

$$R_t = \propto_1 D_{1t} + \propto_2 D_{2t} + \propto_3 D_{3t} + \propto_4 D_{4t} + \propto_5 D_{5t} + \sum_{1=i}^{n} \propto_i R_{t=i} + \varepsilon_t \text{.....(9)}$$

Where:

$R_t =$ represents returns on a selected index

$D_{1t}, D_{2t}, D_{3t}, D_{4t}$ and D_{5t} = the dummy variables for Monday, Tuesday, Wednesday, Thursday, and Friday respectively at time t.

Therefore, if the p-values of the coefficients of the dummy variables corresponding to the day of the week are statistically significance, it will imply that there will be presence of the DOW effect, if not statistically significant means that no presence of the DOW effect. In addition, if the coefficient is negative, it means a negative effect and the *vice versa*.

Variance Equation

$$h_t^2 = V_c + V_1 D_1 + V_2 D_2 + V_4 D_4 + V_5 D_5 + V_{J1} \varepsilon_{t-1}^2 + V_{1b} h_{t-1}^2 \text{.......................... (10)}$$

Where:

V_c = the constant and for this study the value of V_3 solves the dummy trap.

D_1 = Monday

D_2 = Tuesday

D_4 = Thursday

D_5 = Friday.

The statistically significant coefficients of the dummy variables from both the mean and variance equations show whether there is presence of the DOW effect. The statistical significance of specific, some, or all on any day of the week, it implies that the DOW effect is present and vice versa. A negative coefficient shows that the returns were negative and vice versa.

EGARCH Model

The EGARCH model was suggested by Nelson (1991) and performs better than the GARCH (*p, q*) model. This is because the EGARCH model does not require the condition of non-negativity. That is, it does not require a situation that ensure positive coefficients. The EGARCH model also allows the capturing of the asymmetric characteristics of data. This is against the GARCH (*p, q*) model that is based on symmetric assumption. Thus, the EGARCH model provides the opportunity for the leverage effect, which usually indicates the level of response of the investors to market news. Therefore, in line with Chinzara and Slyper (2010), Osarumwense (2015) and Ndako (2013), our study used the EGARCH model. Brooks (2014) and Ndako (2013) showed that the variance equation of this model comprises of specifications on the DOW effect in the volatility equation given in (12)

Mean Equation

$$R_t = \sum_{i=1}^{p} \Phi_i D_{it} + \sum_{j=1}^{p} \emptyset_j R_{t-j} + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (11)$$

Where:

R_t = Daily index Returns

Φ_i = the Monday return (intercept)

D_{i1}= daily dummies for *i* = 2, 3…5.

Thus if *i* = 1, $D_1$is Monday dummy, through to *i=5*, D_{i5} being Friday, and Φ_1 to Φ_5 are the coefficients of daily dummies. R_{t-j} is the Autoregressive (AR) term for returns and consequently, $\emptyset_j$ represents the coefficients for lagged return values where *j* is the lag- length (*j*=1, 2…*p)*and $\varepsilon_t$is the error term which is normally distributed. In testing for the presence of the DOW, the null hypothesis states that there is no DOW effect and this mathematically represented as follows:

$$H_0 : D_1 = D_2 = D_3 = D_4 = D_5 = 0$$

$$H_1 : D_1 \neq D_2 \neq D_3 \neq D_4 \neq D_5 \neq 0$$

The study was interested in the coefficients of the dummy variables and their signs (positive or negative). Positive signs imply positive returns and vice versa. If the $D_{jt}{}'s$ are statistically significant, the null hypothesis is rejected implying the presence of the DOW effect (daily seasonality).

Variance Equation

$$\text{Log}\,(\sigma^2) = V_C + V_{D1} D_{1t} + V_{D2} D_{2t} + V_{D_4} D_{4t} + V_{D_5} D_{5t} + \log(\sigma^2) = \omega + \beta.\log(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}} \propto \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}}} - \sqrt{\frac{2}{\pi}} \right] \ldots\ldots\ldots\ldots\ldots \quad (12)$$

$\propto + \beta < 1$, $\gamma < 0$, if volatility is asymmetric.

Where:

ω =is a constant or intercept,

γ = represents the asymmetric component,

β = represents the GARCH term (lagged values of the conditional variance),

$\propto$= is the coefficient of the absolute values of the difference between the standardized residual,

$\text{Log}\ (\sigma^2)$ =log of the conditional variance (dependant variable),

$\frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}}}$ = is the standardized residual

$\left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}}} - \sqrt{\frac{2}{\pi}}\right]$ =Expected value of the standardized residuals.

The co-efficient of D_{1t}, D_{2t}, D_{4t} and D_{5t} dummy variables represent the size and direction of the effect of each day of the week on volatility. The commonly used significance levels for statistical inference are 10%, 5% and 1%.

The presents of the DOW effect is shown when the p-values of the coefficients of the dummy values are statically significance, that is, the p values will be less than 0.01 or 0.05 or 0.1. Otherwise, this implies that if there is no statistical significance and consequenlty the DOW effect does not exist.

TGARCH Model

The TGARCH model was first introduced by Zakoian (1990.), later improved by Glosten *et al.* (1993). It has a structure similar to the symmetric GARCH model with one exception. The TGARCH includes a parameter γ in the variance equation to indicate the existence of a differentiated behavior in the volatility against positive and negative shocks. Similar to Apolinario *et al.* (2006), this study applied the TGARCH model. The generalized mean and variance equations incorporated in a T-ARCH model are given in Eq. (13)

Mean Equation

$$r_{it}=\beta_1 D_{1t} + \beta_2 D_{2t} + \beta_3 D_{3t} + \beta_4 D_{4t} + \beta_5 D_5 + \sum_{j=1}^{4} \beta_{j+5} r_{t-j} + \varepsilon_t \text{............} (13)$$

Where:

r_{it} = is the i^{th} returns of the t^{th} daily yield of the financial asset

D_{jt} = is the j^th^ dummy variable which take on the value 1 if the corresponding return of the t^th^ day is Monday, Tuesday, Wednesday, Thursday or Friday, respectively and 0 otherwise

β_j = is the j^th^ Beta coefficient which represent the average return for each day of the week

ε_t = is the error term.

The corresponding hypotheses are given as:

$$H_0 : D_1 = D_2 = D_3 = D_4 = D_5 = 0$$

$$H_1 : D_1 \neq D_2 \neq D_3 \neq D_4 \neq D_5 \neq 0$$

If the F- statistic of each D_{jt} is statistically significant, the null hypothesis will be rejected implying the presence of the DOW effect (daily seasonality).

Variance Equation

The variance equation is given in (14):

$$h_t = \omega + \beta h_{t-1} + \alpha \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} + \sum_{m=1}^{5} \omega_m D_m \text{ ....(14)}$$

Where:

ω = is a constant term representing the Wednesday dummy to solve the dummy trap problem, $\omega_m D_m$ = the coefficients of exogenous dummy variables for Monday, Tuesday, Thursday and Friday

ε_{t-1}^2 = the ARCH term

h_{t-1} = the GARCH term

I_{t-1} = the indicator function (for asymmetric effect).

GARCH in Mean Model

Engle, Lilien and Robins (1987) proposed to extend the basic GARCH model so that the conditional volatility can generate a risk premium which is part of the expected returns. This extended GARCH model is often referred to as GARCH-in-the-mean (GARCH-M) model and is specified in (15) and (16).

Mean Equation

$$\gamma_t = \mu + \sum_{i=1}^{5} \mu_t D_t + \delta\sigma_{t-1} + u_t, u_t \sim \text{N}(0, \sigma_t^2) \qquad (15)$$

Where:

γ_t = the mean return

$\mu_t D_t$= are the dummy variables and their coefficients representing 5 days Monday to Friday

Variance Equation

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 + \sum_{t=1}^{5} \alpha_t D_t \qquad (16)$$

Where:

δ = is a risk premium.

σ_{t-1}^2 = is the conditional variance term

$\alpha_t D_t$ = are the dummy variables and their coefficients representing Monday, Tuesday, Thursday and Friday.

The statistical significance coefficients of the dummy variables from both mean and variance equations show whether there is presence of the DOW effect. The significance of a dummy variable on a particular day, it implies that the DOW effect is present and the vice versa is true. If the sign of the coefficient is negative, it shows that the returns were negative, and *vice versa*.

4.3.4 Diagnostics Tests of the models

To ensure the reliability of the results, model diagnostic tests were conducted as part of statistical inference to check the robustness of the model estimation process. The diagnostic tests include the Ljung-Box Q-test (for testing autocorrelation) and ARCH LM test (for testing any remaining ARCH effects). If the model is adequate, then the standardised residuals should be exhibiting no significant serial correlation and no ARCH effects (Brooks, 2014). These tests are identical to those described previously in section 4.3.1 – the difference being that they are now performed on the regression residuals to ascertain the suitability of the model as opposed to on the returns to understand the characteristics of the series being examined.

Ljung-Box Q-test (Check Residuals for Autocorrelation) and ARCH LM test (Check Residuals for Conditional Heteroscedasticity)

To assess the general validity of the mean and variance equations, two tests were performed: the Ljung-Box test for autocorrelation on the standardized residuals (for the mean returns) as well as the squared standardized residuals (for variance of returns). Default number of lags (36 lags) was considered in each case with the null hypothesis stating that there is no autocorrelation against the alternative that there is autocorrelation. Brooks (2014) put forward that this test provides a means of testing for auto-correlation within the ARCH model's standardized residuals. When the ARCH models have been estimated, auto-correlation must be tested within the residuals. In time series models, the innovation process is assumed to be uncorrelated.

After fitting a model, inference on residuals is done to check them for any autocorrelation. More formally, a Ljung-Box Q-test was conducted on the residual series with the null hypothesis of jointly zero autocorrelations up to lag *m*, against the alternative that at least one non-zero autocorrelation exists. Should the p-values be significant at all levels of significance (0.01, 0.05, 0.1) then, H_0: k = 0 the null hypothesis should be rejected, meaning that the GARCH model had not captured the auto-correlation. Similarly, using the p-values symbols (* for 0.01, ** for 0.05 and *** for 0.1) implies that the results are statistically significant. 10% level of significance was included following other DOW effect studies (Ting, 2012), (Urquhart and McGroarty, 2016), (Evanthia, 2017) and (Rich, 2018).

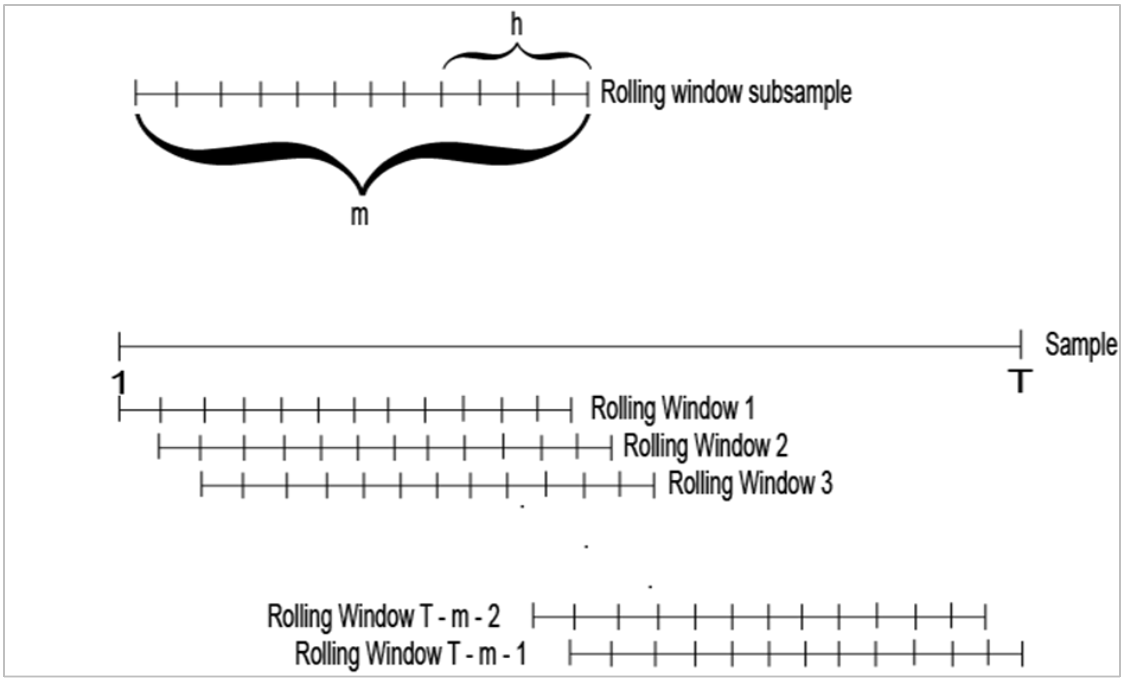
4.5 The Rolling Window Approach

The second objective examines the changes of the DOW effect over time and how this effect fluctuates over time. This was done with best fitted model estimated in each subsample as the focus was on examining the nature of the DOW effect in different sub-periods there by observing any changes over time. Examining DOW effects through a rolling window is relatively new to the calendar anomalies field. The rolling window approach can be used to assess the changes of stock market calendar effects over time folowing studies done by Ting (2012), Urquhart and McGroarty (2016), Evanthia (2017) and Rich (2018).

The two characteristics of the rolling window approach are the so-called rolling window size and the step size. The window size is the number of consecutive observations per estimate and this essentially depends on the sample size. Ting (2012) expalined that if the studied time period is short, the window size will be quite small (one year or less) while for longer sample sizes, the determination of the window size may be bigger (more than one year). Rich (2018) added that longer time horizons tend to yield smoother estimates. Step size is the number of increments between successive rolling windows. The concept of rolling window analysis is illustrated in Figure 4-1.

This study followed Evanthia (2017) by choosing a three-year window length rolling 1-year forward. Evanthia (2017) also added that the motivation for a smaller window size is increased sensitivity to changes in the underlying process from which one will be sampling. The motivation for a larger window size is decreased noise due to small sample size. The size of the rolling window is related to the timescales of the system (response times). For systems with fast timescales short windows can be appropriate, whereas systems with slow timescales require longer rolling windows for the metrics to be able to capture changes in the signature of the time series. Also, the shorter the rolling window is, the less accurate the estimate of the metric becomes. Again, just like with filtering, there is no golden rule for the right size of the rolling window (Rich, 2018). There is a trade-off between having a long enough window to estimate the metrics and short enough to have a sufficient number of windows in order to be able to derive a trend.

Figure 4-1: The Concept of the Rolling Window Analysis



Source : Siddiqui et al. (2011)

If the sample size is T and the the required window size is *m* with a step size *k*, the procedure incorporates the key feature of a rolling window approach of having a fixed length of the window. The first subsample containts the first *m* observations, the second contains the observations from 1+*k* through *m*+*k*, the third from 1+2*k* through *m*+2*k* etc. the concept of rolling window estimation are shown in the figure 4-1.

A regression is estimated upon each subsample and the estimates of each subsample later compared. This study used 3-year rolling windows (following Evanthia (2017) with a study period of 27 years.)) to provide enough observations to generate reliable results while also providing enough results to analyse how the calendar anomalies could have behaved over time.

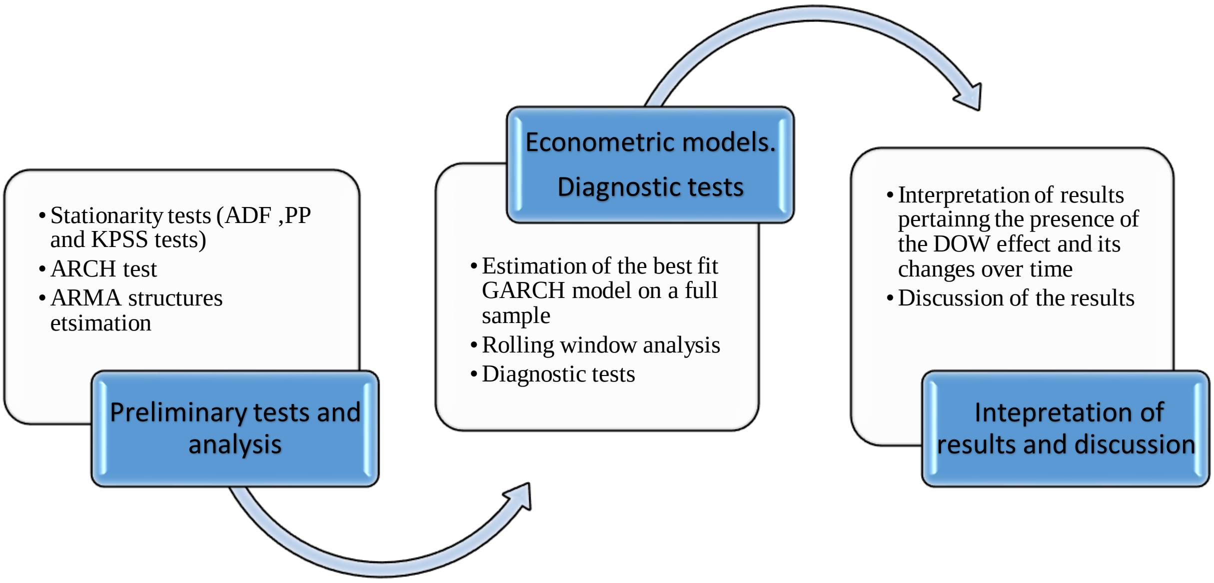
If the p-values of the coefficients of the dummy variables in both the mean and variance equation are significant, it implies that the DOW effect is present and *vice versa*. As the AMH theory assumes that stock are not constantly efficient and therefore market efficiency evolves with time. It is expected to see the presence or absence of the DOW effect in some windows or sub-periods throughout the study period, but not necessarily in all windows or sub-periods.

This study applied a rolling window analysis using the selected best fit model on each sub-sample in order to examine any changes of the DOW effect in the selected four indices. This was motivated following the work of Urquhart and McGroarty (2014), and Chatzitzisi *et al.* (2019). These studies were able to detect the presence or absence of the DOW seasonality in some of the rolling windows in their analysis.

4.6 Chapter Summary

This chapter discussed the methods and data employed in this study. As indicated in study by Urquhart and McGroarty (2016) and Rich (2018) models were used to assess the presence of the DOW effect on the JSE specifically on four indices (Large, medium, small and AltX) over the period 1995 to 2019. The study followed the rolling window method from Rich (2018) to examine the changes of the DOW effect over time was also outlined. The next chapter details the results from the data analysis conducted following the procedures summarised in figure 4-2.

Figure 4-2: Summary of the Research Methodology



Source: Author's Formulation

CHAPTER 5 : DATA ANALYSIS AND FINDINGS

5.1 Introduction

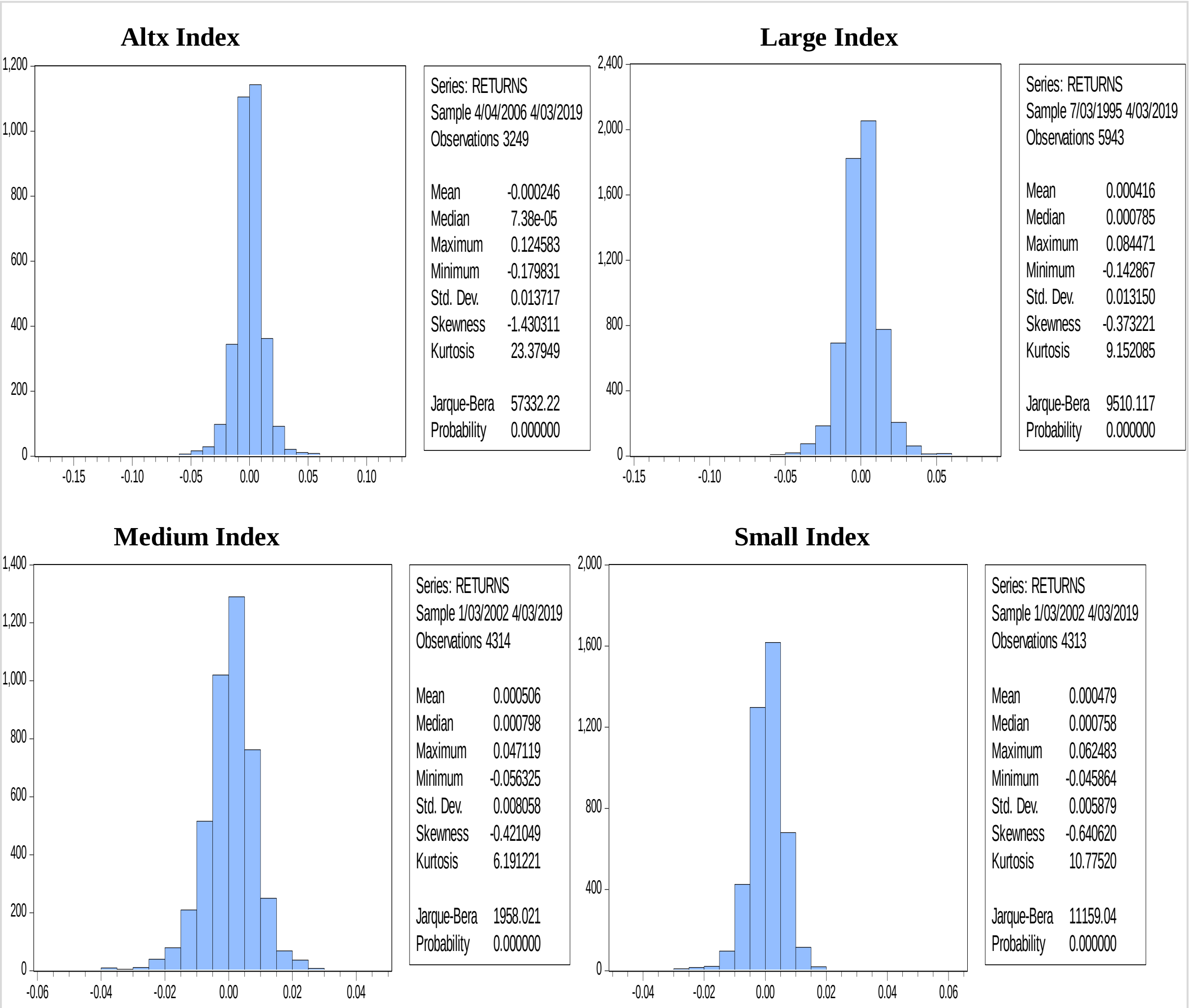
This chapter reports the results from the data analysis that employed the methods discussed in chapter 4. The research objectives were to investigate whether the DOW effect existed, to examine whether existence of the DOW effect (if it exists) differs across company sizes utilising the capitalised indices' returns and their volatility. Finally, to test whether the DOW effect changes over time capturing shocks that may have effects on stock returns (such as the global financial crisis). This chapter is organised as follows: firstly, the statistical analysis in this study began with the presentation of descriptive statistics, with the aid of visuals of the return series, which helped to summarize the data in a meaningful way. This was followed by the findings concerning the existence of the DOW anomaly across company size were reviewed and thereafter the analysis of the individual index returns and their volatility was presented. Lastly, the evidence uncovering the change of the DOW effect in index returns and their volatility on the JSE are discussed.

5.1.1 Descriptive Statistics Analysis

The descriptive statistics contain the summary mean, standard deviation, skewness, and kurtosis of each of the indices' daily log returns. These summary statistics provide an initial look at the dataset; however, further tests to confirm the existence of any anomalies were conducted. A total of 5943, 4314, 4313 and 3429 observations for the large, medium, small and AltX indices' daily log returns were studied from the year in which each index was introduced. Figure 5-1 shows histograms of each index for the full sample.

The results in figure 5-1 show tall and narrow distributions, an indication that log-return series' do not follow a normal distribution. The mean returns showed that the Altx index had on average negative returns (-0.00246) while the other three indices (Large, Medium and Small) had on average positive returns (0.00416, 0.000506 and 0.000479 respectively). The Jarque-Bera test values of 57332.22, 9510.77, 1958.021 and 11159.04 for AltX, large, medium and small indices respectively indicated a significant departure from normality for each of the indices. The skewness coefficients of all four indices were negative indicating that the distribution was negatively skewed, a common feature of equity returns (Engle and Patton, 2001). Selected indices' returns are negatively skewed indicating that more of the index daily returns were below the mean than above the mean, which is the most documented nature of log-returns of stocks (Mandimika and Chinzara, 2010).

Figure 5-1: Descriptive Statistics of the Four Indices Return Series



Source: EViews Outputs

The kurtosis coefficients measure the thickness of the tails of the distribution. The results showed that these were all above the expected value of 3, implying an extreme deviation from normality. According to Patton (2001), kurtosis values ranging from 4 to 50 are considered to be an extreme deviation from normality. Kurtosis for all the indices was above three, the value for a normal distribution, revealing that the distributions of the returns on these indices had very peaked means and fatter tails than a normal distribution. This means that more returns were concentrated around the mean and at the extremes; that is, returns tended to be close to the mean or far away from the mean. Consistent with these observations regarding skewness and kurtosis, the JB tests rejected the null hypothesis of a normal distribution for each series, as shown by the significant statistics in figure 5-1. This result taken in conjunction with the measure of kurtosis in excess of three suggests that the log-return series are leptokurtic. Overall, these results provide evidence that the JSE indices exhibited characteristics that are common with financial series (Mandimika and Chinzara, 2010).

A further individual assessment of the descriptive statistics was conducted for each index on each specific day of the week, and it these are displayed in tables 5-1 to 5-4. The purpose of this stage is to determine if, within each index, the data characteristics differ from day to day.

Table 5-1: Descriptive Statistics for Large Index

Statistics	Monday	Tuesday	Wednesday	Thursday	Friday
Mean	0.0625	-0.0150	0.0677	0.0075	0.0127
S. deviation	0.3957	0.4018	0.4013	0.4018	0.3993
Skewness	1.5449	1.4812	1.4864	1.4812	1.5074
Kurtosis	3.3867	3.1934	3.2094	3.1939	3.2722
Observations	5943	5943	5943	5943	5943

Table 5.1 offers daily results for the large index. Notably, Wednesday has the highest mean returns (0.0677) during the study period, while Tuesday shows the lowest negative returns figure (-.00150). The standard deviation that shows the volatility of the returns was the highest on Tuesdays and Thursdays (0.401840.) but lowest on Mondays (0.395730). The kurtosis was slightly above the expected figure of three on all the days of the week while the skewness is positive at an average of 1.5 on all the days of the week. This indicated that the returns were not normally distributed and a non-parametric test will be the best suited for the identification of any seasonality effects.

Table 5-2: Descriptive Statistics for Medium Index

Statistics	Monday	Tuesday	Wednesday	Thursday	Friday
Mean	0.0907	0.0082	0.0922	0.0006	0.0074
S. deviation	0.3955	0.4020	0.4013	0.4020	0.3994
Skewness	1.5475	1.4799	1.4870	1.4799	1.5069
Kurtosis	3.3948	3.1900	3.2112	3.2000	3.2707
Observations	4314	4314	4314	4314	4314

Table 5.2 shows the results for the medium index where Monday and Wednesday showed the highest returns of (0.0907 and 0.0922) while lowest returns were found on Thursdays. Similar

to the large index, the kurtosis was slightly above the expected figure of 3 on all the days of the week while the skewness is positive at an average of 1.5 on all the days of the week. This indicated that the returns were not normally distributed.

Table 5-3: Descriptive Statistics for Small Index

Statistics	Monday	Tuesday	Wednesday	Thursday	Friday
Mean	0.1228	0.0218	0.0913	0.0031	-0.0732
S. deviation	0.3678	0.4025	0.4037	0.4345	0.3923
Skewness	1.5484	1.4828	1.4828	1.4781	1.5092
Kurtosis	3.3977	3.1987	3.1987	3.1846	3.2776
Observations	4313	4313	4313	4313	4313

Table 5.3 shows the results for the small index. It is showing that Monday has the highest mean returns (0.1228) over the study period while Friday had the lowest mean returns of (-0.0732). For a normally distributed series, kurtosis and skewness are expected to be close to 3 and 0 respectively (Brooks, 2014). However, that is not the case with the small index implying that this index's returns is not normally distributed. As mentioned by Mandimika and Chinzara (2010), that financial data is not normally distributed due to volatility (variance not constant) and that is well captured by GARCH models.

Table 5-4: Descriptive Statistics for AtlX Index

Statistics	Monday	Tuesday	Wednesday	Thursday	Friday
Mean	0.0899	-0.0347	0.0907	0.0080	0.0269
S. deviation	0.3954	0.4017	0.4017	0.4022	0.3992
Skewness	1.5484	1.4828	1.4828	1.4781	1.5092
Kurtosis	3.3977	3.1987	3.1987	3.1846	3.2776
Observations	3249	3249	3249	3249	3249

Table 5.4 indicates that AltX index had the highest returns on Wednesdays followed by Mondays (0.0899 and 0.0907) while Tuesdays was the worst day with negative returns of -0.0347. Like all the other indices the kurtosis and skewness values were very similar (3 and 1.5) implying that all the indices were not normally distributed, therefore non- parametric models like GARCH models can be used for estimations.

This study made no conclusion on the existence of the DOW effect in terms of sizes from descriptive statistics as newer, more advanced approaches such as the GARCH models are being preferred. Chinzara and Slyper (2010) Mbululu and Chipeta (2012), Chia (2014) did not use the descriptive statistics in examining the existence of the DOW effect. A recent study by

Obalade and Muzinditsi (2019) supported that descriptive statistics do not show the statistical significance of the DOW effect but rather a general nature or characteristics of the log returns. These studies argued that the descriptive statistics do not account for the volatility aspect of the returns. Further tests were run in order to have a better understanding of the DOW effect in these indices.

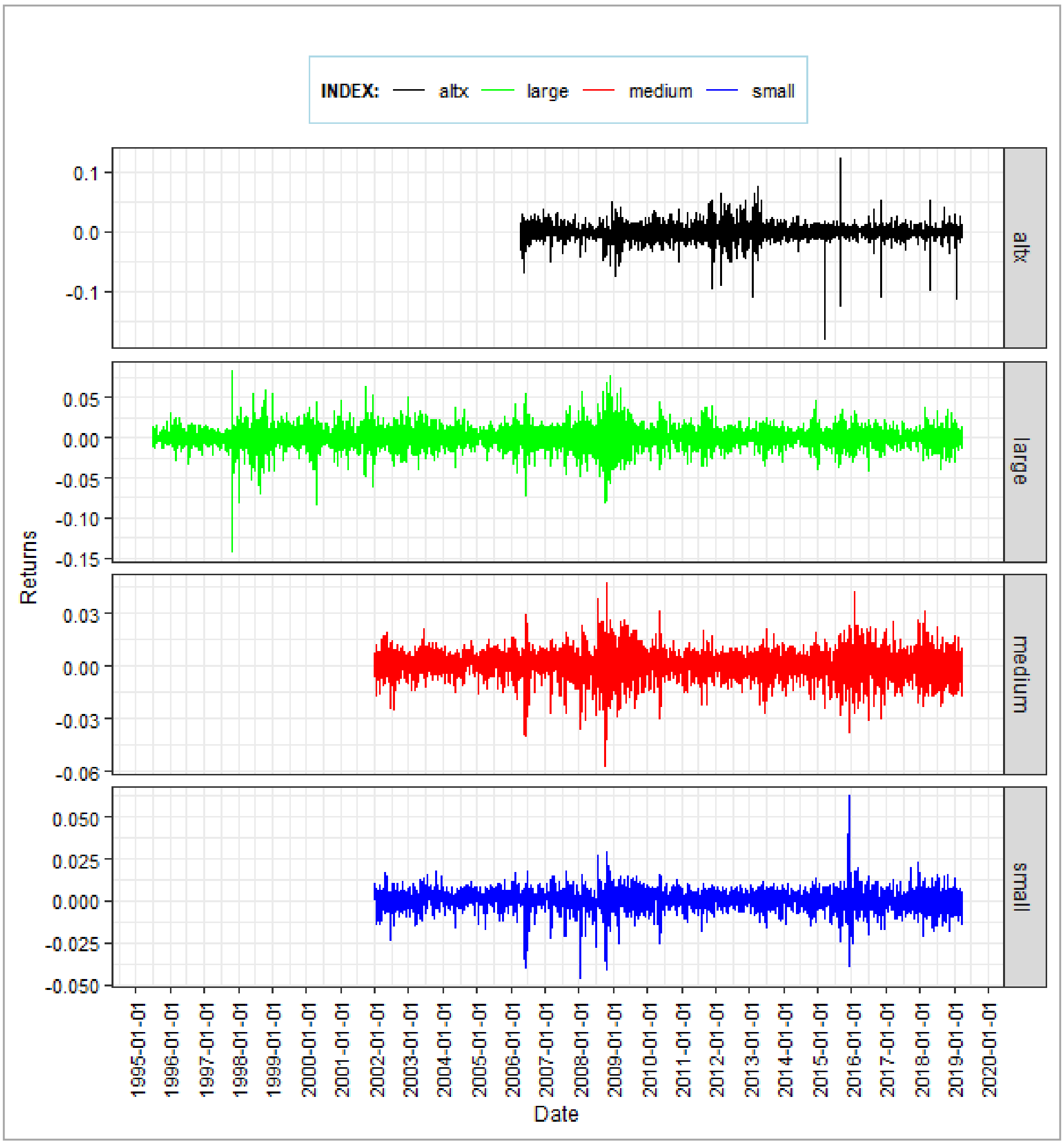
Descriptive statistics section considers preliminary data characteristics and considers if the data characteristics are meeting the prerequisite conditions of the GARCH models. Indices' returns were found to be not normally distributed which is the mostly found characteristic of financial data. However, non-normality characteristic does not affect GARCH model estimations (Brooks, 2014). There are models that require the data to be normally distributed or else the results would regarded as not robust such as all linear models. However, some non-linear models such as GARCH models are able to handle non-normal data (Kaloglou, 2010).

5.1.2 Unit Root (Stationary) Test Results

Visual Stationary Plots

Before estimating the models, it is of paramount importance to examine the stationarity of the returns. Analysis started with graphical plots that all appear to indicate evidence of stationary in the distribution of each index. Figure 5-2 shows that the returns are volatile but stationary, with the volatility revolving around the mean. Also shown is volatility clustering – an expected characteristic of stock returns. These visual plots show that the returns are stationary, a finding that was confirmed by the ADF, KPSS and PP tests, which are presented next.

Figure 5-2: The Visualisation of the Stationary Behaviour



5.1.2 ADF, PP and KPSS Tests Results

Since a time series data is used for this study, a pre-requisite condition for estimating the GARCH models is that of stationarity of the index returns. ADF, PP and the KPSS tests were used to test to ensure that the visual results indicated above were robust. These tests' results suggested that the stationary condition was met for all the four indices as summarised in table 5.5. Recalling that the null hypotheses for both the ADF and PP tests are that there is no stationarity, whilst the KPSS's null hypothesis states that there was stationarity. All the ADF and

PP tests rejected the null hypotheses in favour of the alternative hypothesis that there is stationarity in these indices' series. On the other hand, all the KPSS test results failed to reject the null hypotheses that state that there is evidence of stationarity.

Table 5-5: Stationary Test Results for all the Indices

			Test critical values			
Index size	Test	Test statistic	1% level	5% level	10% level	P-value
LARGE	ADF	-74.0906	-3.4313	-2.8618	-2.5670	0.0001
	PP	-74.1042	-3.4313	-2.8618	-2.5670	0.0001
	KPSS	0.0519	0.7390	0.4630	0.3470	
MEDIUM	ADF	-57.1253	-3.4317	-2.8620	-2.5671	0.0001
	PP	-64.1790	-3.4322	-2.8622	-2.5672	0.0001
	KPSS	0.2713	0.7390	0.4630	0.3470	
SMALL	ADF	-31.8477	-3.4317	-2.8620	-2.5671	0.0001
	PP	-58.8998	-3.4317	-2.8620	-2.5671	0.0001
	KPSS	0.8607	0.7390	0.4630	0.3470	
ALTX	ADF	-64.4598	-3.4322	-2.8622	-2.5672	0.0001
	PP	-64.1790	-3.4322	-2.8622	-2.5672	0.0001
	KPSS	0.2713	0.7390	0.4630	0.3470	

Hence, both the visual displays and the statistical tests provided enough evidence for the suitability of the data to the application of the GARCH models. Chinzara and Slyper (2010) and Orumwense (2015) also support these stationarity results and a recent study by Obalade and Muzindutsi (2019) that log returns are mostly found to be stationary at level.

5.1.3 Serial Correlation and Heteroscedasticity Tests on the Index Returns

In addition to the descriptive statistics, tests for ARCH effects and autocorrelation were done on each of the indices, the results of which are reported in table 5.6.

Table 5-6 : Ljung-Box and ARCH-LM Test Results

	Large	Medium	Small	Altx
LB statistic	79.368*	23.755	116.11**	49.2170*
LB^2 statistic	3765.1*	4290.9*	1386.9*	75.3050*
Breusch-Godfrey LM statistic	0.7043	1.0969	14.9272*	0.0262
Engle ARCH LM statistic	649.3364*	297.0295*	274.9515*	43.0531*

The LB statistic for each of the indices was significant signifying temporal dependencies in the first moment of the distribution of these returns (Koutmos and Saidi, 2001). In order to verify these results, the Breusch-Godfrey serial correlation LM test was also conducted (Godfrey, McAleer and Mckenzie, 1988). The results of this test confirm the presence of serial correlation in returns up to lag order 36 for all the indices since all the test statistics were significant. These results are consistent with the results from the LB test for serial correlation.

The presence of serial correlation in the return's contrasts with the view of stock market informational efficiency as discussed in chapter 1. If markets are, at least weak-form efficient, share prices should fully reflect all available information about future share values such that current prices cannot be used to extrapolate future returns. Efficiency rests on the principle that share prices should be uncorrelated and as such, the presence of serial correlation in returns violates the concept of market efficiency.

The LB statistic for the squared returns is also statistically significant for each index and is substantially higher than the LB statistic for the returns. This suggests that higher order temporal dependencies are more pronounced; an empirical pattern that has been widely documented in high frequency financial time series (Antoniou *et al.*, 2005). This could assist in explaining the leptokurtic distributions observed in the return series in the previous section (Brooks, 2014). The serial correlation evidenced in the squared returns reveals that the second moments of the series are time-varying meaning that there is heteroscedasticity. Moreover, the variance not only varies over time but also follows an autoregressive pattern, giving rise to volatility clustering (periods of high volatility follow periods of high volatility and periods of low volatility follow periods of low volatility). Hence, there is evidence of ARCH effects.

Engle's (1982) ARCH LM test for heteroscedasticity was also conducted on the indices under the null hypothesis of no ARCH effects. The results shown in table 5.6 confirm the presence of ARCH effects, as the LM test statistics for all of the indices were significant. These results are thus consistent with the LB test results on the squared returns and previous findings on the JSE as documented by Brand (2009), Slyper and Chinzara (2010), Mlambo (2013) and Kgosietsile (2015). Given the results of these two tests, the use of a GARCH model in mapping out conditional volatility appears appropriate since GARCH models capture time-varying conditional volatility, which follows an autoregressive process.

5.2 Estimation of ARMA Structure Results

As discussed in chapter 4, after stationarity of returns has been found the ARIMA or ARMA structure is estimated in order to understand the structural characteristics of these stationary returns before estimating the GARCH models. As the difference of ARIMA from ARMA models has been discussed in the previous chapter, log-return series' for all the selected indices show that they follow an ARMA (p, q) model. Therefore, this section shows how the parameters p and q were obtained following Box-Jenkins methodology.

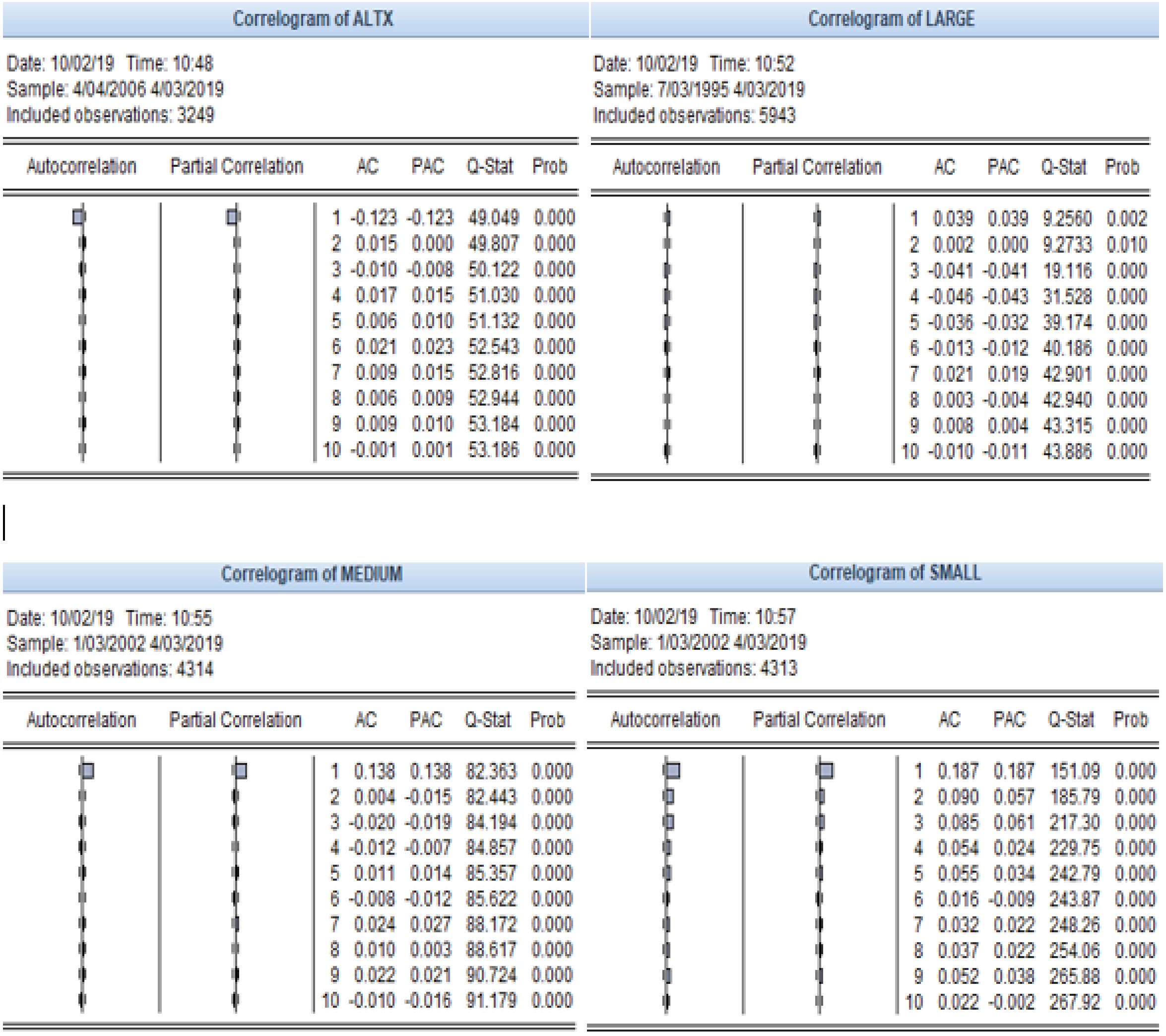
Step 1: Identification Results

Since the log-returns showed that they were stationary at level (or without being differenced first), an ARMA model was appropriate on all the log-return series. From identification criteria, Figure 5-3 shows that the Altx index follows an ARMA (1,1) model, while large index does not show any significant parameters of AR(p) and MA(q), medium index showed an ARMA (1, 1) and the small index shows an ARMA (2, 2). These ARIMA models were parsimonial models that were finally estimated because this was an identification step but not statistically tested (Gujarati and Porter, 2009).

Step 2 selected the best-fitted ARIMA structures through over and under estimating the parsimonial models. In all cases except the large, there is a fair indication of MA and AR terms, as evidenced by the spikes over first Auto-correlation (ACF) and Partial Correlation (PACF) (Gujarati and Porter, 2009). The p-values show that all the ACFs and PACFs are statistically significant, with the major concern at this step being to identify the spikes.

In the section which follows, where the various GARCH models are estimated, the analysis is extended into multiple ARMA structures, to check the robustness of the results / sensitivity of the results to selected ARMA structures and consideration of the statistical significance of the p-vales (shown in table 5-7).

Figure 5-3: Correlograms of the Indices



Correlogram of ALTX

Date: 10/02/19 Time: 10:48
Sample: 4/04/2006 4/03/2019
Included observations: 3249

	AC	PAC	Q-Stat	Prob
1	-0.123	-0.123	49.049	0.000
2	0.015	0.000	49.807	0.000
3	-0.010	-0.008	50.122	0.000
4	0.017	0.015	51.030	0.000
5	0.006	0.010	51.132	0.000
6	0.021	0.023	52.543	0.000
7	0.009	0.015	52.816	0.000
8	0.006	0.009	52.944	0.000
9	0.009	0.010	53.184	0.000
10	-0.001	0.001	53.186	0.000

Correlogram of LARGE

Date: 10/02/19 Time: 10:52
Sample: 7/03/1995 4/03/2019
Included observations: 5943

	AC	PAC	Q-Stat	Prob
1	0.039	0.039	9.2560	0.002
2	0.002	0.000	9.2733	0.010
3	-0.041	-0.041	19.116	0.000
4	-0.046	-0.043	31.528	0.000
5	-0.036	-0.032	39.174	0.000
6	-0.013	-0.012	40.186	0.000
7	0.021	0.019	42.901	0.000
8	0.003	-0.004	42.940	0.000
9	0.008	0.004	43.315	0.000
10	-0.010	-0.011	43.886	0.000

Correlogram of MEDIUM

Date: 10/02/19 Time: 10:55
Sample: 1/03/2002 4/03/2019
Included observations: 4314

	AC	PAC	Q-Stat	Prob
1	0.138	0.138	82.363	0.000
2	0.004	-0.015	82.443	0.000
3	-0.020	-0.019	84.194	0.000
4	-0.012	-0.007	84.857	0.000
5	0.011	0.014	85.357	0.000
6	-0.008	-0.012	85.622	0.000
7	0.024	0.027	88.172	0.000
8	0.010	0.003	88.617	0.000
9	0.022	0.021	90.724	0.000
10	-0.010	-0.016	91.179	0.000

Correlogram of SMALL

Date: 10/02/19 Time: 10:57
Sample: 1/03/2002 4/03/2019
Included observations: 4313

	AC	PAC	Q-Stat	Prob
1	0.187	0.187	151.09	0.000
2	0.090	0.057	185.79	0.000
3	0.085	0.061	217.30	0.000
4	0.054	0.024	229.75	0.000
5	0.055	0.034	242.79	0.000
6	0.016	-0.009	243.87	0.000
7	0.032	0.022	248.26	0.000
8	0.037	0.022	254.06	0.000
9	0.052	0.038	265.88	0.000
10	0.022	-0.002	267.92	0.000

Step 2 and 3: Estimation and Model Checking

In the table that follows, it shows that each of the indices was considered under multiple ARMA structures and the one that generated the smallest AIC and SIC was highlighted in bold text. Kilhamn (2011) explains that the more negative the number is, the smaller it is (it is further from to zero). This is easily demonstrated with a simple everyday life representation, such as temperature (-4 is colder than -3).

Observations were taken daily, with missing trade days incorporated with use of the interpolation method as described in chapter 4. Due to this, one may also consider the economically sensible reality of AR and MA terms in terms of number of days. JSE is a relatively liquid market, where longer term (multi-day) persistence is less likely to be observed.

Table 5-7: Selection of the Appropriate ARMA Model

	Model	P-values	AIC	SIC	Adjusted R^2
Large	ARMA(1,1)	0.9779, 0.9210	-5.8254	-5.8221	0.0012
	ARMA(1,2)	0.0024, 0.8873	-5.8254	-5.8221	0.0012
	ARMA(1,3)	0.0036, 0.0019	-5.8268	-5.8234	0.0027
	ARMA(2,1)	0.8020, 0.0023	-5.8254	-5.8220	0.0012
	ARMA(2,2)	0.0090, 0.0068	-5.8241	-5.8207	-0.0001
	ARMA(2,3)	0.8902, 0.0012	-5.8255	-5.8222	0.0013
	ARMA(3,1)	**0.0025, 0.0034**	**-5.8270**	**-5.8236**	**0.0131**
	ARMA(3,2)	0.0017, 0.8754	-5.8253	-5.8220	0.0013
	ARMA(3,3)	0.2925, 0.2179	-5.8256	-5.8222	0.0015
Medium	ARMA(1,1)	0.6173, 0.4334	-6.8223	-6.8179	0.0188
	ARMA(1,2)	0.0000, 0.4082	-6.8223	-6.8178	0.0187
	ARMA(1,3)	0.0000, 0.1841	-6.8224	-6.8180	0.0190
	ARMA(2,1)	0.6547, 0.0000	-6.8221	-6.8177	0.0187
	ARMA(2,2)	0.0001, 0.0001	-6.8034	-6.7990	0.0002
	ARMA(2,3)	0.6243, 0.1605	-6.8032	-6.7987	0.0000
	ARMA(3,1)	**0.0022, 0.0000**	**-6.8225**	**-6.8181**	**0.0191**
	ARMA(3,2)	0.1664, 0.6181	-6.8031	-6.7987	-0.0001
	ARMA(3,3)	0.7852, 0.7554	-6.8031	-6.7987	0.0001
Small	**ARMA(1,1)**	**0.0000, 0.0000**	**-7.4764**	**-7.4720**	**0.0413**
	ARMA(1,2)	0.0000, 0.0051	-7.4712	-7.4668	0.0363
	ARMA(1,3)	0.0000, 0.0000	-7.4735	-7.4691	0.0385
	ARMA(2,1)	0.0000, 0.0000	-7.4713	-7.4669	0.0365
	ARMA(2,2)	0.0000, 0.0000	-7.4485	-7.4440	0.0142
	ARMA(2,3)	0.0000, 0.0000	-7.4461	-7.4417	0.0119
	ARMA(3,1)	0.0000, 0.0000	-7.4697	-7.4653	0.0351
	ARMA(3,2)	0.0000, 0.0000	-7.4456	-7.4411	0.0116
	ARMA(3,3)	0.0000, 0.0000	-7.4452	-7.4407	0.0112
AltX	ARMA(1,1)	0.4048, 0.9733	-5.7537	-5.7481	0.0144
	ARMA(1,2)	0.0000, 0.9553	-5.7537	-5.7481	0.0144
	ARMA(1,3)	0.0000, 0.7389	-5.7537	-5.7481	0.0145
	ARMA(2,1)	**0.0093, 0.0000**	**-5.7538**	**-5.7482**	**0.0146**
	ARMA(2,2)	0.0000, 0.0000	-5.7434	-5.7378	0.0044
	ARMA(2,3)	0.4164, 0.6681	-5.7387	-5.7330	-0.0003
	ARMA(3,1)	0.7277, 0.0000	-5.7540	-5.7484	0.0143
	ARMA(3,2)	0.6434, 0.4169	-5.7392	-5.7336	-0.0003
	ARMA(3,3)	0.5697, 0.5899	-5.7392	-5.7336	-0.0003

Table 5-7 shows the results of the estimated ARMA models. The results concluded that the appropriate model for the large log return series was ARMA (3, 1) as all coefficients were significant, AIC, SIC were at their minimum, with the highest adjusted R^2. For medium log return series, ARMA (3, 1) also seen to be the more appropriate model as all the coefficients were significant, AIC and SIC were at their minimum with highest adjusted R^2. ARMA (1, 1) fitted the best ofor the small index while ARMA (2, 1) proved to more appropriate for the AltX index. Therefore, these ARMA structures were then used in the following section to select the best-fit model amongst the types of GARCH models considered here (taken from those more widely used in the previous DOW effect literature).

5.3 Selection of the Best-Fit Model

All the four models were estimated on a full sample period and the results are summarised in Table 5-7 below. The results show the best model fitted to the GARCH, TGARCH, EGARCH and GARCH in Mean models. The Akaike information criterion (AIC), Schwarz information criterion (SIC) and the Log-Likelihood criteria were used as the selection criteria for the best model fit. This study follows studies done by Chinzara and Slyper (2010) and Hasan (2017) on how the best GARCH model was selected among the basic GARCH (p, q) and other extensions of GARCH models.

Table 5-8: Summarised Selection Criterion of the Best Fitting Model

Size	Model	AIC	SC	Log-L
ALTX	GARCH(2, 1)	-6.186335	-6.160110	10063.70
	TGARCH(2, 1)	-6.186001	-6.157903	10064.16
	EGARCH(2, 1)	**-6.208608**	**-6.180510**	**10100.88**
	GARCH in Mean(2, 1)	-6.185908	-6.157810	10064.01
LARGE	GARCH(3, 1)	-6.137295	-6.120410	18251.97
	TGARCH(3, 1)	-6.150218	-6.132207	18291.37
	EGARCH(3, 1)	**-6.152191**	**-6.134180**	**18297.24**
	GARCH in Mean(3,1)	-6.137963	-6.119952	18254.96
MEDIUM	GARCH(3, 1)	-7.032327	-7.010180	15183.73
	TGARCH(3, 1)	**-7.036785**	**-7.013161**	**15194.35**
	EGARCH(3, 1)	-7.034582	-7.010958	15189.59
	GARCH in Mean(3, 1)	-7.032028	-7.008404	15184.08
SMALL	GARCH(1, 1)	-7.662214	-7.643015	16536.56
	TGARCH(1, 1)	**-7.664071**	**-7.643396**	**16541.57**
	EGARCH(1, 1)	-7.662079	-7.641404	16537.27
	GARCH in Mean(1, 1)	-7.663510	-7.642835	16540.36

The results showed that EGARCH (2, 1) and EGARCH (3, 1) models better fitted the AltX and the large index respectively and TGARCH (3, 1) and TGARCH (1, 1) better fitted medium and small indices respectively. These had the lowest values for the AIC and SIC and the highest Log likelihood values. All the coefficients were negative so the most negative values are regarded as the smallest or lowest. To answer the first research question that was to test if the DOW effect exists across firm size, the above-mentioned models were used to estimate the results. From the methodology, equation (13) and (14) were estimated for medium and small indices and equation (11) and (12), for AltX and large indices were estimated and applying the appropriate parameters p and q.

In order to allow for further comparability, ARMA (1, 1) was also employed as a normal base of all the four chosen models. The previous studies have shown that many authors simply used ARMA (1, 1) parameters and no other ARMA parameters. Osarumwense (2015) used various

GARCH models but did not specifically fit the ARMA structures. To increase the comparabilty of those results with this current study, ARMA (1,1) was estimated for all the selected models (GARCH, TGARCH, EGARCH and GARCH in mean. As Hansen and Lunde (2001) explained that GARCH (1, 1) is frequently found to be the best model. But to contribute to the literature, formal tests were done to find the best fiiting models given some log-returns' series in the South African stock market context. Table 5-9 below shows the results from the ARMA(1, 1) structure as the base DOW effect analyis using GARCH (1, 1), TGARCH (1, 1), EGARCH (1, 1) and GARCH in mean (1, 1) and their diagnostic tests results.

Table 5-9 does show that the DOW effect exists less in large index as indicated by few statistical significance of positive Thursday effect from the GARCH, TGARCH and EGARCH models. The results also indicate more presence of the DOW effect in the medium, small and AltX index and therefore implying that the DOW effect is found mostly in small to medium companies. However, these results cannot be used to conclude on the findings due to fact that these ARMA (1, 1) structures failed the diagnostics tests rendering them unfit for the log-return series. Some models failed to capture the serial auto correlation and the ARCH effects. As explained in chapter 4, Brooks (2014) explained that if the model is able to capture all the serial correlation and ARCH effects, therefore the residuals must not show any presence of serial correlation and ARCH effects. That is not shown in the p-values of the Q-statistics (serial correlation test) and F- statistics (ARCH effects test) as they are statistically insignificant (more than 5% level of significance).

Therefore, results in table 5-9 shows that ARMA (1, 1) failed to fully capture all the ARCH effects and serial autocorrelation. For the medium index, the ARMA (1, 1) structure on all the four selected models are able to capture all the ARCH effect but fails to capture serial correlation as indicated by the statistical significance of the LB statistics. The small index has a similar case with medium however; TGARCH (1, 1) passed all the three diagnostic tests.

Table 5-9: DOW Effect Results Using ARMA (1, 1) as the Normal Base

		Mon	Tue	Wed	Thu	Fri
Mean Equation						
Large	GARCH (1, 1)	0.0137	0.0316	0.0547	0.0960*	0.0373
	TGARCH (1, 1)	0.0111	0.0610	0.0117	0.0599**	0.0124
	EGARCH (1, 1)	0.0119	-0.0628	0.0146	0.0644**	0.0951
	GARCH in M (1, 1)	0.0147	-0.0214	0.0159	0.0567	0.0678
Medium	GARCH (1, 1)	0.0105	0.0632*	0.0635***	0.0189*	0.0120*
	TGARCH (1, 1)	0.0246	0.0528**	0.0574**	0.0106*	0.0115*
	EGARCH (1, 1)	-0.0114	0.0508**	0.0593***	0.0170*	0.0921*
	GARCH in M (1, 1)	0.0166	0.0699*	0.0711**	0.0263*	0.0187*
Small	GARCH (1, 1)	0.0747	0.0409**	0.0632*	0.0240*	0.0355*
	TGARCH (1, 1)	-0.0551	0.0238	0.0496*	0.0187*	0.0205*
	EGARCH (1, 1)	-0.0951	0.0348**	0.0539*	0.0158*	0.0180*
	GARCH in M (1, 1)	0.0971	0.0429	0.0653*	0.0263*	0.0375*
AltX	GARCH (1, 1)	-0.0484	-0.0239*	0.0183	-0.0140	0.0133*
	TGARCH (1, 1)	-0.0463	-0.0798*	0.0457	-0.0760	0.0440*
	EGARCH (1, 1)	-0.0138	-0.0560*	0.0691	-0.0107	0.0982*
	GARCH in M (1, 1)	-0.0463	-0.0796*	0.0457	-0.0059***	0.0441*
Variance Equation						
Large	GARCH (1, 1)	-4.53E-06	-7.50E-06		-7.17E-06	-2.89E-05*
	TGARCH (1, 1)	-8.95E-06**	-9.45E-06**		-1.21E-05**	-2.87E-05*
	EGARCH (1, 1)	-0.080895	-0.123943**		-0.15902*	-0.236911*
	GARCH in M (1, 1)	-4.78E-06	-7.48E-06		-7.15E-06	-2.90E-05*
Medium	GARCH (1, 1)	-1.02E-06	-6.55E-06		-4.80E-06	-7.65E-06
	TGARCH (1, 1)	-2.26E-06	-6.52E-06**		-5.77E-06	-7.66E-06*
	EGARCH (1, 1)	-0.007380	-0.180947**		-0.085108	-0.181268**
	GARCH in M (1, 1)	-9.94E-07	-6.55E-06**		-4.77E-06	-7.63E-06**
Small	GARCH (1, 1)	1.68E-06	-2.41E-06		5.79E-07	-2.20E-06
	TGARCH (1, 1)	1.82E-06	-1.65E-06		1.22E-06	-2.57E-06
	EGARCH (1, 1)	0.148653**	-0.098561		0.157724**	-0.10622***
	GARCH in M (1, 1)	1.68E-06	-2.41E-06		5.83E-07	-2.21E-06
AltX	GARCH (1, 1)	3.37E-05	7.54E-05		4.17E-05	5.08E-05
	TGARCH (1, 1)	4.26E-05*	7.97E-05*		4.30E-05*	4.66E-05*
	EGARCH (1, 1)	0.284886*	0.368188*		0.373805*	0.375025*
	GARCH in M (1, 1)	4.26E-05*	7.97E-05*		4.30E-05*	4.66E-05*

Diagnostic Tests

	LB statistic	LB^2 statistic	ARCH LM statistic
Large			
GARCH (1, 1)	26.026	17.881	2.0329
TGARCH (1, 1)	3.9973	1.1864	1.9028
EGARCH (1, 1)	3.2596	9.4151	3.0993*
GARCH in M (1, 1)	1.7932	8.0900	2.3446*
Medium			
GARCH (1, 1)	81.956*	1.9988	1.2801
TGARCH (1, 1)	84.416*	1.5107	0.7370
EGARCH (1, 1)	85.533*	4.3131**	1.2761
GARCH in M (1, 1)	81.530*	2.0603	1.3801
Small			
GARCH (1, 1)	8.9875*	4.4199	0.0259
TGARCH (1, 1)	7.8117	6.6184	1.5354
EGARCH (1, 1)	6.9278	21.373*	2.2079*
GARCH in M (1, 1)	8.7667	0.092***	0.7027
AltX			
GARCH (1, 1)	16.626*	0.1770	0.7157
TGARCH (1, 1)	19.355*	0.0725	0.4137
EGARCH (1, 1)	19.157*	0.0298	0.9714
GARCH in M (1, 1)	19.356*	0.0724	0.4012

5.4 Analysis of the DOW Effect Based on Best Fitting Models

To answer the first research question, as to whether there is an existence of the DOW effect in returns and volatility of each of the selected stock indices (company size) from the full sample. Table 5-10 shows the results from the full sample based on the best fitting models presented in table 5-8.

Table 5-10: Results of Each Index from the Full Sample

Mean Equation					
	Mon	Tue	Wed	Thu	Fri
Large	0.0013*	0.0001	0.0001	0.0007*	0.0001
Medium	-4.62E-05	0.0004*	0.0010**	0.0015*	0.0014*
Small	0.0002***	0.0005*	0.0007*	0.0012*	0.0013*
AltX	-0.0001*	-0.0004	0.0004	8.1E-05	0.0014*
Variance Equation					
Large	-0.0578	-0.0864		-0.1197	-0.1887
Medium	0.0129	-0.1027		-0.0566	-0.151*
Small	0.1721	-0.1225		0.1611	-0.1105
AltX	0.2320**	0.0666		0.0059	0.1192

Diagnostic Tests	LB statistic	LB^2 statistic	ARCH LM statistic
Large	32.2630	78.5800	6.9878
Medium	38.521	25.9500	1.0850
Small	44.9890	36.0070	7.8944
AltX	31.3130	4.7093	0.0230

Significance levels: * 1%, ** 5% and *** 10%, LB and LB^2 denote the Ljung-Box statistics for the 36 lags of the indices distributed as χ^2 with n degrees of freedom where n is the number of lags.

Large Index

The estimated coefficients of the dummy variables in the mean equation of the large index showed positive returns on all days of the week; however, only Monday and Thursday were significant (at the 1% level) implying the existence of positive Monday and Thursday effect. Moreover, Monday was observed to be the day with highest returns of 0.0013. Volatility of returns showed non-existence of the DOW effect as none of the coefficients were statistically insignificant. This implies that, the DOW effect was present in the mean equation but absent in the variance equation. This does not go in line with the risk and return relationship which assumes that high returns are associated with more risk (high volatility) (Sinha, 1994). Hence, this is an indication that the DOW effect can be taken advantage of to earn abnormal returns in mean returns only for the large index (large capitalised companies). Some results shows that mean returns were obtained regardless of the nature of volatility present (Brooks, 2014). This is also in line with the previous study by Plimsoll *et al.* (2013) about finding the existence of the DOW effect in the means and none in the volatility of returns.

Medium Index

The medium stock index showed statistically significant (at 1% level) positive returns from Tuesday to Friday whilst having a statistically insignificant negative Monday effect. Thursday had the highest returns of 0.0015 for the week. An opposite pattern was observed in the volatility of returns where Monday had a positive effect although insignificant while Tuesday to Friday showed negative volatility effect with Friday being the most negative and statistically significant. Therefore, it can be concluded that the medium index had a positive Tuesday, Wednesday, Thursday and Friday in the mean returns and a negative Friday effect in the volatility of the returns, therefore the DOW effect can be exploited.

Small Index

Similar to the medium stock index, the small index showed significant positive Monday to Thursday and slight (10% level of significance) Friday positive effects with the highest returns being observed on Friday. In the variance equation, positive volatility effect was observed on Monday and Thursday while negative effect was observed on Tuesday and Friday but were not statistically significant implying the non-existence of the DOW effect. Therefore, it can be concluded that for small companies, investors or traders can follow these observed trends in the mean returns only to earn abnormal returns. While no DOW effect is found in the volatility of returns and therefore traders or investors cannot take advantage of it.

AltX Index

AltX index showed significant negative Monday and Tuesday effects and positive Wednesday to Friday effects and highest returns being shown on Friday. Thus, supporting the existing literature that the DOW effect is when firms yield negative returns in the beginning of the week and positive towards the end of the week. The AltX index constitutes small to medium companies and the notion the DOW effect is mostly found in companies with low capitalisation is supported. In the volatility aspect, a positive effect was observed on all the days of the week but only positive Monday effect was statistically significant. Therefore, it can be concluded from this study found that the AltX index followed the expected pattern of having negative returns at the beginning of the week and then positive and high towards the end of the week.

The first research objective of the study examine whether the DOW effect existence differ across firm size in South African stock market, results obtained concluded that the DOW effect exists fairly less in the large index and medium index and more in small and AltX index. Theoretical literature and other previous studies (Bhana (1985), Coutts and Sheikh (2002), Mbululu and Chipeta (2012), Obalade and Muzinditsi (2019) and others have postulated that the DOW effect is characterised by negative returns in the beginning of the week and positive returns at the end of the week. However, thus not what has been exhibited in the results, only AltX index follows the pattern outlined in the literature. Results from the large, medium and small index showed positive Monday and Thursday effect, medium index showed positive Tuesday to Friday effects. Lastly, small index showed fair less positive Monday effect at 10% level of significant and strong positive Tuesday to Friday effects at 1% level of significance.

Since, the AltX index includes small companies and it has supported the notion that the DOW effect does exists in companies with low capitalisation. Previous studies on the JSE, Atsin and Ocran (2015) and Plimsoll *et al.* (2013) examined the All Share index and found that the DOW effect does not exists in the South African stock market. Therefore, this study helps the investors to understand that the DOW effect does exists but the nature of the anomaly differ according to company sizes as exhibited by the results.

Residual Diagnostics

Residuals from the four estimated models were examined for serial dependency. The test statistics were insignificant for all the indices, which means that the mean and variance equations were correctly specified due to the absence of serial autocorrelation in the mean returns and their variance. The results of Engle's (1982) ARCH test shown in the lower panel of table 5.8 confirm that there were no ARCH effects present in the standardised residuals of any of the indices as these test statistics were insignificant. Thus, the mean and variance equations of these indices were correctly specified using the EGARCH (2, 1) and EGARCH (3, 1) models better fitted the AltX and the large index respectively and TGARCH (3, 1) and TGARCH (1, 1) specifications.

5.5 Analysis from the Rolling Window Results

The second objective was to examine any changes of the DOW effect over the 24-year period of this full sample across firm size. The AltX, medium and small indices were introduced later, resulting in less than 24 years (and less rolling windows) than the large index. The study examines fluctuations of the DOW effect over time, in terms of its appearance and disappearance within each given rolling window (cyclical pattern). The results were estimated for a three-year window length rolling 1-year forward following Evanthia (2017)'s methodology. The idea behind the rolling window method enables one to look at underlying changes of the DOW effect on a shorter time scale. The knowledge of the changes of the DOW effect over time allow investors use different strategies that suits different nature of the DOW anomaly within a particular period. This was also supported by Lo (2004) and Obalade and Muzindutsi (2019) who stated that some investment strategies are successful in some periods yet likely to be unsuccessful in other times.

5.5.1 ARIMA Estimates and Best-Fit Model for Each Sub-Period

The objective was to examine the changes of the DOW effect over time, and so it was necessary to estimate the best ARIMA structure for each window to find the best-fit model for each window or sub-period. Looking back at figure 5-2, the return series' were stable but in some periods showed some spikes that could imply that return series' were not stationary during that time. However, the impact of this is potentially getting lost in examining the series as a whole. Considering the effect of financial crisis between 2007 and 2009 and other market factors, figure 5-2 showed some instability of returns in some periods in all the four indices as shown by the spikes.

In order to capture these periods of instability in a more detailed manner, which allows changes in the market between one periods to the next, a rolling window is used to consider multiple shorter periods. A formal test was done to estimate the best parameters p, d, and q through R software. The *fit (.)* command selects an ARIMA (p, d, and q) by considering the AIC and BIC values generated to determine the best combination of parameters. The lower these values, the better the model (Zhang, 2018).

Tables 5-11 to 5-14 show the best fitting models for each of the rolling window or sub-period. The results showed that the ARIMA structures were indeed changing over time leading to different models being used in each sub-period to accurately capture the data characteristics of a particular point in time. The *d* parameter seems to have been stable in the large index showing stationarity throughout the whole sample period showing stability over time. The medium index show those two out of 16 sub-periods needed the first difference implying that the returns were not stationary during those times. The medium index's periods of non-stationary were during the financial crisis. The small index showed four out of 16 sub-periods that also needed the first difference implying that the series was not stationary during the financial crisis periods as well.

Interestingly, the AltX index showed that the first four out 12 sub-periods were not stationary but became constantly stationary afterwards. The AltX is the newest index of the four considered in this study, and so those earlier years also represent a market which was more thinly traded, and less liquid, and so it is not surprising that the initial years are showing results which indicate a period of less stability.

Therefore, this is an interesting finding to the existing empirical research showing that the impact of less stable periods of the markets are almost certainly contributing to the lack of consensus in these DOW-based research studies. That is, both the sampling period, and the nature of the firms (in this instance size) being considered are going to reach different conclusions. While not a central objective, the use of this particular aspect of this dissertation's analysis does provide some clarity on some of the elements that need careful consideration for those seeking to employ calendar effects in their trading strategies.

Table 5-11: ARMA Structures for the Large Index

Window	p	d	q	**GARCH** (AIC, BIC, HQIC)	**EGARCH** (AIC, BIC, HQIC)	**TGARCH** (AIC, BIC, HQIC)	**GARCH in Mean** (AIC, BIC, HQIC)
1995-1997	5	0	0	(-6.669;-6.527;-6.614)	(-6.635;-6.485;-6.577)	**(-6.671;-6.521;-6.613)**	(-6.667;-6.517;-6.609)
1996-1998	0	0	4	(-5.545;-5.434;-5.502)	(-5.956;-5.840;-5.911)	**(-6.046;-5.929;-6.001)**	(-5.563;-5.447;-5.518)
1997-1999	3	0	3	(-5.912;-5.776;-5.860)	(-5.943;-5.801;-5.889)	(-5.946;-5.804;-5.891)	**(-5.950;-5.808;-5.895)**
1998-2000	0	0	3	(-5.606;-5.507;-5.567)	(-5.705;-5.600;-5.664)	**(-5.711;-5.606;-5.671)**	(-5.541;-5.436;-5.500)
1999-2001	3	0	0	**(-5.902;-5.803;-5.864)**	(-5.871;-5.765;-5.830)	(-5.899;-5.794;-5.859)	(-5.900;-5.794;-5.859)
2000-2002	3	0	2	(-5.798;-5.674;-5.750)	**(-5.812;-5.682;-5.762)**	(-5.799;-5.669;-5.749)	(-5.800;-5.670;-5.750)
2001-2003	3	0	0	**(-5.902;-5.803;-5.864)**	(-5.871;-5.765;-5.830)	(-5.899;-5.794;-5.859)	(-5.900;-5.794;-5.859)
2002-2004	3	0	0	**(-5.902;-5.803;-5.864)**	(-5.871;-5.765;-5.830)	(-5.899;-5.794;-5.859)	(-5.900;-5.794;-5.859)
2003-2005	1	0	2	(-6.336;-6.237;-6.298)	**(-6.349;-6.245;-6.309)**	(-6.349;-6.244;-6.309)	(-6.333;-6.229;-6.293)
2004-2006	1	0	1	(-6.262;-6.175;-6.228)	**(-6.269;-6.176;-6.233)**	(-6.265;-6.173;-6.230)	(-6.259;-6.167;-6.223)
2005-2007	0	0	1	(-5.892;-5.818;-5.864)	(-6.042;-5.962;-6.012)	**(-6.093;-6.013;-6.062)**	(-5.906;-5.825;-5.875)
2006-2008	0	0	1	(-5.892;-5.818;-5.864)	(-6.042;-5.962;-6.012)	**(-6.093;-6.013;-6.062)**	(-5.906;-5.825;-5.875)
2007-2009	3	0	1	(-5.388;-5.277;-5.346)	(-5.412;-5.295;-5.367)	**(-5.414;-5.297;-5.369)**	(-5.386;-5.269;-5.341)
2008-2010	0	0	1	(-5.892;-5.818;-5.864)	(-6.042;-5.962;-6.012)	**(-6.093;-6.013;-6.062)**	(-5.906;-5.825;-5.875)
2009-2011	0	0	1	(-5.892;-5.818;-5.864)	(-6.042;-5.962;-6.012)	**(-6.093;-6.013;-6.062)**	(-5.906;-5.825;-5.875)
2010-2012	0	0	1	(-5.892;-5.818;-5.864)	(-6.042;-5.962;-6.012)	**(-6.093;-6.013;-6.062)**	(-5.906;-5.825;-5.875)
2011-2013	0	0	2	(-6.243;-6.157;-6.210)	(-6.362;-6.269;-6.326)	**(-6.397;-6.305;-6.362)**	(-6.254;-6.162;-6.218)
2012-2014	2	0	1	(-6.664;-6.566;-6.626)	(-6.686;-6.581;-6.645)	**(-6.701;-6.596;-6.661)**	(-6.663;-6.558;-6.623)
2013-2015	2	0	0	(-6.362;-6.269;-6.326)	(-6.361;-6.263;-6.323)	**(-6.373;-6.275;-6.335)**	(-6.359;-6.261;-6.321)
2014-2016	2	0	2	(-6.339;-6.228;-6.296)	**(-6.407;-6.290;-6.362)**	(-6.380;-6.262;-6.334)	(-6.339;-6.221;-6.293)
2015-2017	3	0	2	(-6.461;-6.337;-6.413)	**(-6.504;-6.374;-6.454)**	(-6.489;-6.359;-6.439)	(-6.458;-6.328;-6.408)
2016-2018	3	0	4	(-6.402;-6.253;-6.345)	**(-6.442;-6.287;-6.382)**	(-6.433;-6.278;-6.374)	(-6.401;-6.246;-6.341)
2017-2019	0	0	1	(-5.892;-5.818;-5.864)	(-6.042;-5.962;-6.012)	**(-6.093;-6.013;-6.062)**	(-5.906;-5.825;-5.875)

Table 5-12: ARMA Structures for the Medium index

Window	p	d	q	GARCH (AIC, BIC, HQIC)	EGARCH (AIC, BIC, HQIC)	TGARCH (AIC, BIC, HQIC)	GARCH in Mean (AIC, BIC, HQIC)
2002-2004	1	0	3	(-7.595;-7.484;-7.552)	**(-7.608;-7.491;-7.563)**	(-7.593;-7.476;-7.548)	(-7.599;-7.482;-7.554)
2003-2005	1	0	2	**(-7.708;-7.609;-7.670)**	(-7.705;-7.600;-7.665)	(-7.709;-7.604;-7.668)	(-7.708;-7.603;-7.668)
2004-2006	0	0	1	(-7.279;-7.205;-7.250)	(-7.386;-7.306;-7.355)	**(-7.502;-7.422;-7.471)**	(-7.277;-7.197;-7.246)
2005-2007	0	0	1	(-7.279;-7.205;-7.250)	(-7.386;-7.306;-7.355)	**(-7.502;-7.422;-7.471)**	(-7.277;-7.197;-7.246)
2006-2008	3	1	0	**(-6.540;-6.435;-6.495)**	(-6.458;-6.352;-6.417)	(-6.531;-6.426;-6.490)	(-6.537;-6.432;-6.496)
2007-2009	1	0	0	**(-6.295;-6.217;-6.262)**	(-6.258;-6.178;-6.227)	(-6.293;-6.213;-6.262)	(-6.289;-6.209;-6.259)
2008-2010	1	1	0	**(-6.295;-6.217;-6.262)**	(-6.258;-6.178;-6.227)	(-6.293;-6.213;-6.262)	(-6.289;-6.209;-6.259)
2009-2011	3	0	2	(-6.972;-6.848;-6.924)	(-6.993;-6.862;-6.942)	**(-7.000;-6.870;-6.950)**	(-6.973;-6.843;-6.923)
2010-2012	1	0	0	**(-6.295;-6.217;-6.262)**	(-6.258;-6.178;-6.227)	(-6.293;-6.213;-6.262)	(-6.289;-6.209;-6.259)
2011-2013	1	0	0	**(-6.295;-6.217;-6.262)**	(-6.258;-6.178;-6.227)	(-6.293;-6.213;-6.262)	(-6.289;-6.209;-6.259)
2012-2014	2	0	2	(-7.407;-7.295;-7.364)	**(-7.439;-7.322;-7.394)**	(-7.408;-7.291;-7.363)	(-7.405;-7.288;-7.360)
2013-2015	0	0	1	(-7.279;-7.205;-7.250)	(-7.386;-7.306;-7.355)	**(-7.502;-7.422;-7.471)**	(-7.277;-7.197;-7.246)
2014-2016	0	0	2	(-6.613;-6.527;-6.580)	(-6.614;-6.522;-6.578)	**(-6.774;-6.682;-6.739)**	(-6.638;-6.546;-6.603)
2015-2017	0	0	1	(-7.279;-7.205;-7.250)	(-7.386;-7.306;-7.355)	**(-7.502;-7.422;-7.471)**	(-7.277;-7.197;-7.246)
2016-2018	2	0	0	**(-6.568;-6.482;-6.535)**	(-6.559;-6.466;-6.523)	(-6.567;-6.474;-6.531)	(-6.572;-6.479;-6.536)
2017-2019	0	0	1	(-7.279;-7.205;-7.250)	(-7.386;-7.306;-7.355)	**(-7.502;-7.422;-7.471)**	(-7.277;-7.197;-7.246)

Table 5-13: ARMA Structures for the Small index

Window	p	d	q	GARCH (AIC, BIC, HQIC)	EGARCH (AIC, BIC, HQIC)	TGARCH (AIC, BIC, HQIC)	GARCH in Mean (AIC, BIC, HQIC)
2002-2004	0	1	4	(-7.862;-7.751;-7.819)	**(-7.869;-7.752;-7.824)**	(-7.867;-7.750;-7.822)	(-7.867;-7.749;-7.821)
2003-2005	1	0	2	(-8.054;-7.956;-8.016)	**(-8.059;-7.957;-8.019)**	(-8.052;-7.947;-8.012)	(-8.055;-7.950;-8.014)
2004-2006	0	0	3	(-7.768;-7.670;-7.730)	(-7.909;-7.804;-7.869)	**(-7.990;-7.885;-7.950)**	(-7.772;-7.667;-7.732)
2005-2007	0	0	3	(-7.587;-7.488;-7.549)	(-7.658;-7.553;-7.618)	**(-7.738;-7.634;-7.698)**	(-7.584;-7.479;-7.544)
2006-2008	0	1	2	(-7.050;-6.964;-7.017)	(-7.055;-6.962;-7.019)	**(-7.316;-7.223;-7.280)**	(-7.062;-6.970;-7.026)
2007-2009	1	0	2	(-7.231;-7.132;-7.193)	(-7.258;-7.154;-7.218)	**(-7.265;-7.160;-7.224)**	(-7.231;-7.126;-7.190)
2008-2010	0	1	3	(-7.768;-7.670;-7.730)	(-7.909;-7.804;-7.869)	**(-7.990;-7.885;-7.950)**	(-7.772;-7.667;-7.732)
2009-2011	3	0	2	(-7.691;-7.567;-7.643)	(-7.692;-7.562;-7.642)	**(-7.694;-7.565;-7.644)**	(-7.688;-7.559;-7.638)
2010-2012	2	0	2	(-8.080;-7.969;-8.037)	(-8.073;-7.956;-8.028)	**(-8.087;-7.969;-8.042)**	(-8.086;-7.969;-8.041)
2011-2013	5	1	0	(-8.089;-7.997;-8.054)	(-8.105;-8.006;-8.067)	**(-8.110;-8.012;-8.072)**	(-8.096;-7.997;-8.058)
2012-2014	0	0	1	(-8.105;-8.031;-8.077)	(-8.134;-8.054;-8.103)	**(-8.151;-8.071;-8.120)**	(-8.103;-8.022;-8.072)
2013-2015	1	0	1	**(-7.696;-7.610;-7.663)**	(-7.681;-7.589;-7.646)	(-7.693;-7.601;-7.658)	(-7.694;-7.601;-7.658)
2014-2016	1	0	0	**(-7.381;-7.307;-7.353)**	(-7.358;-7.278;-7.327)	(-7.379;-7.298;-7.348)	(-7.379;-7.299;-7.348)
2015-2017	1	0	0	**(-7.381;-7.307;-7.353)**	(-7.358;-7.278;-7.327)	(-7.379;-7.298;-7.348)	(-7.379;-7.299;-7.348)
2016-2018	3	1	0	**(-7.379;-7.276;-7.337)**	(-7.356;-7.251;-7.316)	(-7.373;-7.267;-7.332)	(-7.376;-7.270;-7.335)
2017-2019	1	0	1	**(-7.696;-7.610;-7.663)**	(-7.681;-7.589;-7.646)	(-7.693;-7.601;-7.658)	(-7.694;-7.601;-7.658)

Table 5-14: ARMA Structures for the AltX index

Window	p	d	q	**GARCH** (AIC, BIC, HQIC)	**EGARCH** (AIC, BIC, HQIC)	**TGARCH** (AIC, BIC, HQIC)	**GARCH in Mean** (AIC, BIC, HQIC)
2006-2008	0	1	1	(-6.017;-5.937;-5.986)	(-6.035;-5.950;-6.002)	**(-6.098;-6.012;-6.065)**	(-6.014;-5.928;-5.981)
2007-2009	0	1	1	(-6.017;-5.937;-5.986)	(-6.035;-5.950;-6.002)	**(-6.098;-6.012;-6.065)**	(-6.014;-5.928;-5.981)
2008-2010	5	1	1	(-5.932;-5.796;-5.880)	**(-5.944;-5.802;-5.889)**	(-5.937;-5.795;-5.882)	(-5.939;-5.797;-5.884)
2009-2011	2	1	4	**(-5.733;-5.597;-5.681)**	(-5.717;-5.575;-5.662)	(-5.733;-5.591;-5.678)	(-5.726;-5.584;-5.672)
2010-2012	0	0	1	(-6.017;-5.937;-5.986)	(-6.035;-5.950;-6.002)	**(-6.098;-6.012;-6.065)**	(-6.014;-5.928;-5.981)
2011-2013	1	0	0	(-5.331;-5.256;-5.302)	**(-5.339;-5.258;-5.308)**	(-5.331;-5.251;-5.300)	(-5.328;-5.248;-5.297)
2012-2014	2	0	2	(-5.815;-5.704;-5.772)	**(-5.834;-5.717;-5.789)**	(-5.817;-5.700;-5.772)	(-5.815;-5.697;-5.769)
2013-2015	2	0	0	(-5.869;-5.783;-5.836)	(-5.858;-5.765;-5.822)	(-5.845;-5.753;-5.810)	**(-5.885;-5.793;-5.849)**
2014-2016	0	0	1	(-6.017;-5.937;-5.986)	(-6.035;-5.950;-6.002)	**(-6.098;-6.012;-6.065)**	(-6.014;-5.928;-5.981)
2015-2017	0	0	1	(-6.017;-5.937;-5.986)	(-6.035;-5.950;-6.002)	**(-6.098;-6.012;-6.065)**	(-6.014;-5.928;-5.981)
2016-2018	2	0	2	(-6.674;-6.562;-6.631)	**(-6.752;-6.635;-6.707)**	(-6.517;-6.400;-6.472)	(-6.671;-6.554;-6.626)
2017-2019	0	0	1	(-6.017;-5.937;-5.986)	(-6.035;-5.950;-6.002)	**(-6.098;-6.012;-6.065)**	(-6.014;-5.928;-5.981)

5.5.2 Changes of the DOW over Time

Tables 5-15 to 5-18 show the estimates for each day of the week, in each rolling window. This stage of analysis allows detail to be inferred regarding these relationships.

Table 5-15 shows the rolling window results for the large index and has 23 windows. Examining the changes in returns and volatility, the results showed that Monday returns were positive but only few sub-periods (windows) which were statistically significant. In 1998-2000, 2001-2003, and 2008-2010 showed the presence of a positive Monday effect that is a complete opposite of what has been mostly found in the literature. Theoretically, DOW effect is characterised by negative returns on Monday and positive returns on Friday. The large index showed positive Thursday and Friday effect in one sup-period (2008-2010). Tuesday and Wednesday returns exhibited a mixture of positive and negative returns over time but none of the returns was statistically significant implying that there was no DOW effect. In this case, DOW effects were present in very few windows, three out of a total 23 windows, which indicates that the DOW effect occurs less frequently in large companies – making it difficult to take of advantage of it.

These results partially support the existing literature on the size effect that the DOW effect does not exist in large companies however, this study found little DOW effect. On the other side, the results support the EMH that it is difficult to earn abnormal profits through patterns of returns thereby concluding that the large index showed that there is efficiency trading in large companies.

Table 5-15: Rolling Window Results for Large Index

Mean Equation					
Window	Mon	Tue	Wed	Thu	Fri
1995-1997	0.0006	6.49E-05	0.0010	0.0002	-0.0008
1996-1998	0.0007	-8.83E-04	0.0001	-0.0001	-0.0031
1997-1999	0.0014	-8.69E-04	0.0008	0.0007	0.0007
1998-2000	0.0030*	-6.16E-04	-0.0003	0.0005	0.0014
1999-2001	0.0033	1.17E-03	-0.0003	0.0020	0.0019
2000-2002	0.0009	3.63E-04	-0.0015	0.0003	-0.0017
2001-2003	0.0017*	6.44E-04	-0.0011	0.0004	0.0022
2002-2004	4.97E-05	7.89E-04	-0.0015	8.75E-05	0.0034
2003-2005	1.87E-03	-3.29E-04	-0.0007	1.47E-03	0.0019
2004-2006	2.01E-03	4.44E-04	0.0006	2.24E-03	0.0035
2005-2007	2.53E-03	-1.05E-03	0.0007	1.55E-03	0.0052
2006-2008	0.0018	0.0012	0.0001	0.0054	-0.0013
2007-2009	0.0005	-0.0052	-0.0042	0.0071	-0.0009
2008-2010	0.0017**	-0.0041	0.0937	0.0017***	0.0034**
2009-2011	0.0063	-0.00036	0.0017	0.0034	-0.0014
2010-2012	0.0023	4.72E-06	0.0008	0.0013	-0.0063
2011-2013	-0.0076	0.0017	7.16E-05	0.0069	-3.55E-06
2012-2014	4.25E-05	0.0011	-0.0003	0.0052	2.70E-05
2013-2015	0.0042	0.0012	-0.0008	0.0023	-0.0020
2014-2016	-7.49E-05	-0.0009	-0.0003	-8.15E-05	-0.0011
2015-2017	0.0006	-0.0036	-2.98E-	-6.06E-06	-0.0023
2016-2018	**0.0023**	**-0.0097**	**-0.0002**	**-0.0024**	**0.0089**
2017-2019	**0.0016**	**0.0011**	**-0.0002**	**-0.0036**	**0.0015**
Variance Equation					
1995-1997	-0.12745	-0.04107		-0.10625	-0.0123
1996-1998	0.01535	0.0505		0.00675	-0.0906
1997-1999	-0.0906	-0.00680		0.05305	-0.0385
1998-2000	-0.0013	-0.0015		-0.0026	-0.0195
1999-2001	0.0004	0.0011*		0.0009	0.2441
2000-2002	0.0011	0.0009		0.0008	0.2847
2001-2003	0.0011	0.0005		0.0010	0.2958
2002-2004	0.0004	-7.02E-05		0.0009	0.3102
2003-2005	0.0003	-0.0004		0.0010	0.2621
2004-2006	-0.0004	-0.0008		0.0005	0.2381
2005-2007	-0.0005	-0.0012		0.0006	0.2993
2006-2008	-0.117	-0.1928		-0.0425	0.0045
2007-2009	0.00402	-0.21103		0.04842	0.11463
2008-2010	0.1881	0.0249		0.27	-0.0166
2009-2011	0.0511	0.068		0.0469	-0.0258*
2010-2012	-0.273	-0.1842		-0.2999	0.0581
2011-2013	0.0503	-0.0202		-0.0521	-0.3239
2012-2014	0.0320	0.0806		-0.0916	-0.0979
2013-2015	-0.0644	0.0174		-0.2222	-0.3208*
2014-2016	-0.0442	-0.2620		-0.4761	-0.4951
2015-2017	0.0974	-0.118		0.1541	-0.0763
2016-2018	**-0.107**	**-0.357**		**-0.2226**	**-0.4029**
2017-2019	**-0.0171**	**-0.0888**		**-0.2064**	**-0.3352**

*Significance levels: * 1%, ** 5% and *** 10%*

In volatility of returns, the results showed almost non-existence of the DOW effect where the statistical significance of the coefficients was found in only three out 23 windows. 1999-2001 showed a positive effect, 2009-2011 and 2013-2015 showed a negative effect. The overall results from the large index supported Plimsoll *et al.*, (2013) in which South Africa was included in the study utilizing the TGARCH model and found no DOW effect on the JSE.

Table 5-16 shows 16 rolling windows for the yearly changes of the DOW effect in the medium stock index. From the mean equation that represents the returns for the index showed that Monday returns were positive and negative. Out of 16 windows, 13 showed the presents of some DOW effects, Monday returns showed both positive and negative returns over time but only negative returns were statistically significant. Tuesday returns revealed also that windows had both positive and negative returns with some windows with both being statistically significant. This shows that positive returns are present in the beginning of the week that had not been found in the previous studies. Wednesday returns showed some few positive effects in only four windows out of 16 windows. Thursday and Friday showed a strong positive effect, as the coefficients in many windows were statistically significant showing the presents of the DOW effect. Overall, the study concluded that the medium index's results showed negative Monday and Tuesday effect and positive Thursday and Friday effect. Moreover, that what was expected and it mostly documented in the empirical literature.

In the volatility of returns, the results showed a little of the DOW effect as only a negative Tuesday effect in the sub-sample 2017-2019. Therefore, this study concluded that the DOW effect does not exist in the volatility of returns medium capitalized companies. Overall, the medium index results partially support the literature on the revealing a positive Friday effect. The interesting view is that Tuesday had both positive and negative effects. Therefore, these results supported Winkelried and Iberico (2015), Dicle and Levendis (2014) as they also found negative Monday effect and positive Friday effect. To add on, the significance of the returns was not constant and the DOW effect existed in other windows and disappeared in other windows thereby supporting the AMH.

Table 5-16: Rolling Window Results for Medium Index

Mean Equation					
Window	Mon	Tue	Wed	Thu	Fri
2002-2004	-0.0010**	0.0004***	0.0004	0.0006	0.0009**
2003-2005	0.0003	0.009***	0.0006	0.0009***	0.0009***
2004-2006	0.0002	0.0006	-0.0006	0.0006	7.47E-05
2005-2007	0.0005	0.0008	-0.0002	0.0007	0.0003***
2006-2008	0.0004	0.0011*	0.0008**	0.0009**	0.2441*
2007-2009	0.0011*	0.0009	0.0003	0.0008*	0.2847*
2008-2010	0.0011*	0.0005	0.0006	0.0010*	0.2958*
2009-2011	0.0004	-7.02E-05	0.0008	0.0009**	0.3102*
2010-2012	0.0003	-0.0004	0.0011**	0.0010**	0.2621*
2011-2013	-0.0004**	-0.0008*	0.0016**	0.0005	0.2381*
2012-2014	-0.0005**	-0.0012*	0.0002	0.0006	0.2993*
2013-2015	-0.0009**	-0.0009***	0.0003	0.0008	0.2701*
2014-2016	-5.44E-05	0.0009***	0.0014**	0.0007	3.56E-06
2015-2017	-0.0010**	0.0004***	0.0004	0.0006	0.0009**
2016-2018	**0.0003**	**0.009*** **	**0.0006**	**0.0009*** **	**0.0009*** **
2017-2019	**0.0002**	**0.0006**	**-0.0006**	**0.0006**	**0.0047***
Variance Equation					
2002-2004	-0.1179	-0.4305		-0.0972	-0.3257
2003-2005	-0.1068	-0.2504		-0.2308	-0.2909
2004-2006	0.0972	-0.0317		-0.0860	-0.1135
2005-2007	-0.2606	0.3906		0.0006	-0.7506
2006-2008	-0.8906	-0.2806		-0.2205	-0.7406
2007-2009	-0.0306	-0.3709		-0.3507	-0.8906
2008-2010	-0.5706	0.1205		-0.0505	-0.6506
2009-2011	-4.3406	-0.9507		-0.1405	-0.4105
2010-2012	-0.1068	-0.2504		-0.2308	-0.0909
2011-2013	0.0972	-0.0317		-0.0860	-0.035
2012-2014	0.0004	0.0011		0.0009	0.0041
2013-2015	0.0011	0.0009		0.0008	0.0047
2014-2016	0.0011	0.0005		0.0010	0.0058
2015-2017	0.0004	-7.02E-05		0.0009	0.0002
2016-2018	**0.0003**	**-0.0004**		**0.001**	**0.0021**
2017-2019	**-0.0004**	**-0.0008***		**0.0005**	**0.0081**

*Significance levels: * 1%, ** 5% and *** 10%*

Table 5-17 had a total number of 16 windows for the small index. The presence of the DOW effect was observed in each of the windows but differing in the day of the week in which they were statistically significant. Monday returns showed negative returns in the beginning of the period only two windows 2002-2004 and 2003-2005. Tuesday showed both positive and negative returns where the anomaly started appearing in 2004-2007 with a positive effect, then disappeared for some years up 2010 but it had switched to a negative trend from 2011-2014. The last 3 sub-periods showed a positive effect and these switching of DOW effect has not been documented in the literature. Thursday and Friday returns showed that all the returns were all positive and it is shown that the presence and the significance of the DOW effect was constant expect the disappearance and appearing over time? This supports the AMH notion that stock market returns tend to change over time that calls for the interested stakeholders to adapt to the changes and act or strategize accordingly.

Table 5-17: Rolling Window Results for the Small Index

Mean Equation					
Window	Mon	Tue	Wed	Thu	Fri
2002-2004	-6.90E-05*	3.55E-05	0.0011*	0.0011**	0.0011**
2003-2005	-0.0002**	0.0004	0.0011*	0.0008**	0.0009**
2004-2006	7.70E-05	0.0011*	0.0009	0.0003	0.0008*
2005-2007	0.0006	0.0011*	0.0005	0.0006**	0.0010*
2006-2008	0.0005	0.0004	-7.02E-05	0.0008***	0.0009**
2007-2009	0.0004	0.0003	-0.0004	0.0011**	0.0010**
2008-2010	-8.11E-05*	-0.0004	-0.0008*	0.0016**	0.0005
2009-2011	0.0004	-7.02E-05	0.0008***	0.0009**	0.0082*
2010-2012	0.0003	-0.0014	0.0011**	0.0010**	0.0071*
2011-2013	-0.0017*	-0.0018*	0.0032**	0.0089	0.0084*
2012-2014	-0.0027**	-0.0012*	0.0002	0.0052	0.0093*
2013-2015	-0.00344*	-0.0014***	0.0003	0.0018	0.0051*
2014-2016	-5.44E-05	0.0017***	0.0014**	0.0027	1.56E-06*
2015-2017	-0.0016**	0.0018***	0.0004	0.0006	0.0021**
2016-2018	**0.0025**	**0.0091*** **	**0.0016**	**0.0019*** **	**0.0011*** **
2017-2019	**0.0011**	**0.0021**	**-0.0034**	**0.0052**	**-7.47E-05**
Variance Equation					
2002-2004	0.0001	0.0004		-0.3320	-0.0752
2003-2005	-0.0014**	-0.0001		-0.2213	-0.0830
2004-2006	-0.0029*	-0.0004		-6.30E-05	-0.0900
2005-2007	-0.0005	-0.3007		-0.1904	-0.2017*
2006-2008	0.3210	-0.2008		-0.4114	-0.2564*
2007-2009	0.2116	-0.1006		-0.6115**	-0.1620*
2008-2010	-0.0005	-0.2006		-0.3217**	-0.1357*
2009-2011	-0.0002	-0.3007		-0.1120*	-0.0815*
2010-2012	-0.0004	-0.1111		-0.1225*	-0.1346*
2011-2013	-0.0005	-0.1302		-0.1519*	-0.0962*
2012-2014	-0.0015*	-5.22E-05		-0.2314*	-0.1354*
2013-2015	-0.0009	-0.0007		-0.3510**	-0.1156*
2014-2016	-0.1068	-0.2504		-0.2308	-0.2909
2015-2017	0.0972	-0.0317		-0.0860	-0.1135
2016-2018	**0.2606**	**0.3906**		**-2.00E-06**	**-1.75E-06**
2017-2019	**0.18906**	**0.2816**		**-1.22E-05**	**-9.74E-06**

*Significance levels: * 1%, ** 5% and *** 10%*

Table 5-18 shows the results of AltX index with 12 rolling windows from the year it was introduced in 2006 to 2019. Monday and Tuesday returns showed both negative and positive returns effect over the sample period; however, not all of them were statistically significant. Statistically significance of the coefficients of the parameters showed the presence of the DOW anomaly and the vice versa.

Table 5-18: Rolling Window Results for AltX Index

Mean Equation					
Window	Mon	Tue	Wed	Thu	Fri
2006-2008	2.5E-03	-1.5E-03*	0.00749	1.55E-03	0.0015**
2007-2009	-0.0018**	0.0002	0.0001	0.0015*	0.0011
2008-2010	-0.0005**	-0.0002*	-0.0004	0.0021**	0.0006
2009-2011	-0.0023**	-0.0011*	0.0937	0.0017***	0.0022**
2010-2012	0.0013	-0.0006*	0.001	0.0004**	0.0011*
2011-2013	-0.0003	4.72E-06	0.0008	0.001	0.0012*
2012-2014	-0.006**	0.0007	7.16E-05	0.0007**	3.55E-06**
2013-2015	4.25E-05	0.0011	-0.0003	0.0005*	2.70E-05*
2014-2016	0.0001	0.0005	-0.0008*	0.0005*	0.0002**
2015-2017	-7.49E-05*	-0.0003*	-0.0003	-8.15E-05	0.0003**
2016-2018	**-0.0003*** **	**-0.0005** **	**-0.0004**	**0.0024***	**-0.0001**
2017-2019	**-0.0023** **	**-0.0011** **	**0.0937**	**0.0017*** **	**0.0022** **
Variance Equation					
2006-2008	0.3032	-0.6396		0.0934	0.1881
2007-2009	0.3452*	0.3657**		-0.1032	0.0511
2008-2010	0.2785	-0.9629		0.0397	-0.273
2009-2011	0.3597	-0.1192		-0.0232	0.0503
2010-2012	0.232	0.1169		0.0031	0.0320
2011-2013	0.9419*	0.2488		0.0213	-0.0644
2012-2014	0.6529**	-0.1707		-0.1934	-0.0442
2013-2015	0.8957	0.1337		-0.0069	0.0974
2014-2016	-0.5628	-0.2248		-0.2645	-0.107
2015-2017	-0.1217	0.3364		-0.0746	-0.0171
2016-2018	**0.1275**	**0.7492** **		**0.1269**	**0.1881**
2017-2019	**-0.7473**	**0.1379** **		**-0.0338**	**0.0511**

*Significance levels: * 1%, ** 5% and *** 10%*

The negative Monday and Tuesday effect were found to be significant in 2007-2009, 2008-2010, 2009-2011, 2012-2014 and 2015-2019 only. There was no DOW effect on Wednesday. Most windows have positive statistically significant Thursday and Friday returns but only few of the windows were not statistically significant meaning the non-existence of the DOW effect.

These results support the AMH hypothesis that the DOW effect evolves over time and it is sometimes present or absent in some other periods. The results from this study were in line with the previous studies by Chang *et al*., (1993) which tested the presence of the DOW effect in China through examining the All Share index returns from 1985 to 1992 employing the OLS model and the results found negative Monday and positive Friday effects.

The volatility of the returns also showed a mixture of positive and negative effects in each day of the week in the sub-sample windows. The presence of the DOW effect is proved by the statistical significance of return coefficient and the *vice versa*, positive Monday and Tuesday effects were present in 2007-2009, 2016 to 2019 and absent in 2011-2014. Therefore, the DOW effect was found to be very small in the volatility of returns where only three windows (2007-2009 and 2016-2019) were statistically significant at 5% level of significance. Therefore, this study can conclude that the AltX index which represents small to medium companies do not follow the EMH hypothesis (having on average equal returns on each day of the week), but rather follows the AMH hypothesis. The reason being that it proved that some days had positive effect, some had negative effect on volatility, and the DOW effect in the returns was appearing and disappearing in some windows over time. This study's results were also in line with Chinzara and Slyper (2010) in which GARCH, TGARCH and EGARCH were utilized from 1995 to 2010. The results showed Negative Monday, positive Friday and little DOW effect in volatility of the returns.

The volatility of returns showed mostly negative effect in different windows but the presence of the DOW effect was found on Thursday and Friday that were statistically significant in many windows showing some persistence. Overall, the results have shown that DOW effect is present in small-capitalised companies but it also changes, as it is sometimes present in other period, disappears, and appears again supporting the AMH hypothesis.

To maximise the understanding of the changes of the DOW effect over time, table 5.17 below shows the summary of the frequency in which DOW effect was present in all the four indices regardless of being positive or negative. The large index shows positive Monday effect in 3 out of 23 windows and none on Tuesdays and Wednesdays. Thursday and Friday had the DOW effect in only one window while one window associated with negative effect in the volatility equation. Therefore, this study concluded that investors trading in large companies might not enjoy the benefits of taking the advantage or arbitraging from the existence of the DOW effect because of its less availability in terms of frequency.

Table 5-19: Summary of the Presence of the DOW Effect in Rolling Windows

	3-yr rolling windows*		Mean equation					Variance equation			
Size	Period	Total	Mon	Tue	Wed	Thu	Fri	Mon	Tue	Thu	Fri
LARGE	1995-2019	23	3	0	0	1	1	0	1	0	0
MEDIUM	2002-2019	16	7	9	4	7	13	0	1	0	0
SMALL	2002-2019	16	7	8	7	9	14	3	0	9	12
ALTX	2006-2019	12	7	7	1	9	9	3	3	0	0

** 1-year increment*

The availability frequency of the DOW effect in the medium, small and the AltX indices were more as compared to the large index. The summary clearly showed the size effect, also commonly called the small- firm effect that is characterised by smaller capitalised firms exhibiting positive returns at the weekend while negative returns in the beginning of the week. The relationship between capitalisation and seasonality is well documented with smaller firms exhibiting positive returns on Friday and negative returns on Monday as compared to larger companies (Chu *et al*., 2004). To add on, this study also concluded that the DOW effect does exist more on the JSE stock returns than in volatility of returns as shown by frequency of appearance in the table 5.17. Atsin and Ocran (2015) also supported the sentiment that the DOW effect is mostly found in small-capitalised companies. Therefore, investors are potentially able to earn abnormal returns in small to medium companies on the JSE by using trading strategies based on DOW effects.

A glance on the DOW effect in recent years that are highlighted in bold texts, thus the last two sub-periods on each of the selected indices. Given the changes in time, it would be prudent for traders not rely too heavily on long-term history; therefore, this study contributes to the literature by showing recent changes. The large index (table 5-15). shows non –existence of the DOW effect in both returns and volatility of those returns from 2016 to 2019 The medium index (table 5-16) shows little existence of the DOW effect from 2016 to 2018 at the statistical significance was conclude at 10% which is fairly not as strong as the 1% and 5% level of significance. However, the existence decreased in the last sub-period in 2017-2019 as the results shows that only positive Friday effect was present and non-existence of the DOW effect in the volatility of returns as well. The small index (table 5-17) shows the existence of the DOW effect from 2016-2018 but 2017-2019 shows its absence. Lastly, the AltX index (table 5-18) shows consistent existence of the DOW effect from 2016-2019 in almost all days of the week but a positive Tuesday effect in volatility in all the two sub-periods (2016-2018 and 2017-

2019). Future research could expand into seeking exactly what period for technical analysis is helpful for DOW in AltX stocks.

5.6 Chapter Summary

In summary, the DOW effect existed on the JSE stock exchange in three out of all the four investigated firm sizes; which are medium, small and AltX not in the large index (companies), particularly more in returns than in the volatility of those returns. The first objective was to examine the existence of the DOW effect using the full sample. The large index showed literally no DOW effect as only very few sub-periods showed its presence that can be a difficult pattern to be followed by traders. Medium index showed positive Tuesday to Friday effects in returns equation and negative Friday effect on volatility. Small index exhibited positive Monday and Friday effects and no DOW effect was found in volatility. Lastly, AtlX index revealed negative Monday, positive Friday effects, and a little positive Monday and Tuesday effect in volatility.

Observing the changes of the DOW in all of these four indices, it was found that the existence of the DOW effect in the medium, small and AtlX index was not constant over time supporting the AMH assumptions. The highest frequency of appearance of the DOW effect was found in the medium, small and the AltX indices confirming the notion that the DOW anomaly is mostly found in companies with low capitalisation. Not all the indices followed the assumed the pattern of the DOW anomaly where Monday returns were negative and a positive Friday effect. On the contrary, the medium index showed some few sub-periods with negative Tuesday effect. The rolling window analysis exhibited that the changes of the DOW effect on the JSE does not follow the concept of EMH but rather the AMH because the DOW effect was not constantly present in the sup-periods. The effect was found in other periods and not found in other periods implying that traders and investors have to adapt to the changing patterns.

CHAPTER 6 : CONCLUSION AND RECOMMANDATIONS

6.1 Review of research objectives

The study strived to examine the DOW effect in different sized indices on the South African stock market. In particular, this study looked at the returns' indices and their volatilities across large, medium, small and AltX indices on the Johannesburg Stock Market. The motivation behind studies that consider the DOW effect is based on exploring if the EMH is supported in various markets around the globe. Some reasons have been given as to what leads to the DOW effect and some international studies have found that the DOW effect is mostly found in medium and small markets or firms with low merchantability in the developed international stock markets. However, less attention has been given to emerging markets like South Africa on examining this sentiment in firm size. Moreover, South African literature has examined DOW effect mostly in stock returns and less in volatility of those returns.

This triggered the interest is this study to explore the JSE indices returns and their volatility in the South African stock market. Another aspect of the DOW effect that is less established in the South Africa literature is the changing nature of the DOW effect over time. One of the recent philosophies such as the AMH is that, investors are urged to adapt and use different strategies that suits the current situation. This concept stretches the EMH theory where the assumptions do not consider that the stock market conditions change over time. However, AMH urges investors to be adaptive; hence, the investment strategies may change over time as well. Hence, the need to examine the existence of the DOW effect in the large, medium, small and AltX indices' returns and their volatility as well as its changes over time.

6.2 A summary of the findings

The following sections provide a summary of how the results were obtained and the main findings pertaining to the two research objectives. The data was obtained from the JSE for the period 1995 - 2019 with the following research questions: 1) is there evidence of the Day of the Week Effect in the Large-cap, Medium-cap, the Small-cap indices' and AltX index returns and their volatility on the JSE? 2) How has the DOW effect changed from 1995 to 2019 across company sizes' returns and volatility on the JSE? In order to answer these research questions, the best models fit were selected from a family of GARCH models namely: the GARCH, EGARCH, TGARCH and GARCH in Mean. Prior to the model fitting, ARCH effects, stationarity and serial correlation were assessed for they are the main conditions to be met before the estimation of the volatility models. The test for stationarity involved visual displays in conjunction with some statistical tests such as the ADF, PP and KPSS. The presence of ARCH effects paved the way for the use of the time series stochastic models to examine the dynamic behaviour of volatility of the returns in the JSE indices data. This study added the comparability on the commonly used ARMA (1, 1) structure as previous studies have shown that many authors simply used ARMA (1, 1) parameters and no other ARMA parameters. Therefore, this study estimated all the four selected GARCH models (GARCH (1, 1), TGARCH (1, 1), EGARCH (1, 1) and GARCH in mean (1, 1) as the normal base. Therefore, with the aid of the AIC, SIC and the Log-L criteria, the ARMA estimations concluded that EGARCH (2.1) and EGARCH (3.1) models better fitted the AltX and the large index respectively and TGARCH (3, 1) and TGARCH (1, 1) better fitted medium and small indices respectively.

Is there evidence of the Day of the Week Effect in the Large-cap, Medium-cap, the Small-cap indices' and AltX index returns and their volatility of returns on the JSE?

Results were drawn from the best-fitted models: EGARCH (2.1) and EGARCH (3.1) models better fitted the AltX and the large index respectively and TGARCH (3, 1) and TGARCH (1, 1) better fitted medium and small indices respectively. The large index showed literally no DOW effect as only very few sub-periods showed its presence that can be a difficult pattern to be followed by traders. The DOW effect was present in the mean equation but absent in the variance equation. This does not go in line with the risk and return relationship which assumes that high returns are associated with more risk (high volatility) (Sinha, 1994). Hence, this is an indication that the DOW effect can be taken advantage of to earn abnormal returns in mean returns only for the large index (large capitalised companies). Some results shows that mean returns were obtained regardless of the nature of volatility present (Brooks, 2014). This is also in line with the previous study by Plimsoll *et al.* (2013) about finding the existence of the DOW effect in the means and none in the volatility of returns.

This study concluded that the medium index had a positive Tuesday, Wednesday, Thursday and Friday in the mean returns and a negative Friday effect in the volatility of the returns, therefore the DOW effect can be exploited. Similar to the medium stock index, the small index showed significant positive Monday to Thursday and slight Friday positive effects with the highest returns being observed on Friday. In the variance equation, positive volatility effect was observed on Monday and Thursday while negative effect was observed on Tuesday and Friday but were not statistically significant implying the non-existence of the DOW effect.

From these findings, it can be concluded that for small companies, investors or traders can follow these observed trends in the mean returns only to earn abnormal returns. While no DOW effect is found in volatility of returns and therefore traders or investors cannot take advantage of it.

AltX index showed significant negative Monday and Tuesday effects and positive Wednesday to Friday effects and highest returns being shown on Friday. Thus, supporting the existing literature that the DOW effect is when firms yield negative returns in the beginning of the week and positive towards the end of the week. The AltX index constitutes small to medium companies and the notion the DOW effect is mostly found in companies with low capitalisation is supported. In the volatility aspect, a positive effect was observed on all the days of the week but only positive Monday effect was statistically significant. Therefore, it can be concluded from this study found that the AltX index followed the expected pattern of having negative returns at the beginning of the week and then positive and high towards the end of the week.

Theoretical literature and other previous studies (Bhana (1985), Coutts and Sheikh (2002), Mbululu and Chipeta (2012), Obalade and Muzinditsi (2019) and others have postulated that the DOW effect is characterised by negative returns in the beginning of the week and positive returns at the end of the week. However, thus not what has been exhibited in the results, only AltX index follows the pattern outlined in the literature. Since, the AltX index includes small companies and it has supported the notion that the DOW effect does exists in companies with low capitalisation. Previous studies on the JSE, Atsin and Ocran (2015) and Plimsoll *et al.* (2013) examined the All Share index and found that the DOW effect does not exists in the South African stock market. Therefore, this study helps the investors to understand that the DOW effect does exists but the nature of the anomaly differ according to company sizes as exhibited by the results.

How has the DOW effect changed from 1995 to 2019 across company sizes on the JSE?

The second objective was to examine the changes of the DOW in all of the selected four indices were examined over time. A rolling window analysis method was employed in order to examine the appearance and disappearance of the DOW effect over time (cyclical pattern). The rolling window analysis was employed because Evanthia (2017) argued that some information lost when examining the DOW effect on a full sample. Therefore, the same concept was considered in the South African stock market. The results showed almost non-existence of the DOW effect in the large index in both returns and volatility but it was present in the medium and more in small and AtlX index. However, the existence the DOW effect was not constant over time supporting the AMH assumptions that stock market conditions change over time so the return patterns Lo (2004). The highest frequencies of the appearance of the DOW effect were found in the medium, small and the AltX indices respectively confirming the notion that the DOW anomaly is mostly found in companies with low capitalisation. Not all the indices followed the assumed pattern of the DOW anomaly, where Monday returns were negative and a positive Friday effect. On the contrary, the medium index showed some few sub-periods with negative Tuesday effect. The rolling window analysis exhibited that the changes of the DOW effect on the JSE did not follow the concept of EMH but rather the AMH because the DOW effect was not constantly present in the sup-periods. The effect was found in some other periods implying that traders and investors have to adapt to the changing patterns.

As this study, contribute to the literature by showing the changes of the DOW effect during recent years from 2016 to 2019. The DOW effect seem to be disappearing in the medium and small indices but consistently present in the AltX index. The Altx index contains small to medium firms and that confirm the notion that the DOW effect is mostly found in small-capitalised firms. Information about the changes of the DOW effect over time is also important to all financial stakeholders, as the results have shown that trading or investing on stocks basing on the EMH assumptions does not exist on the JSE. The DOW effect exists on the JSE and it appears and disappears in some periods. Therefore, this study have shown the periods in the DOW effect exits, investors and traders are encouraged to follow the patterns to earn abnormal returns.

Implications of the findings of this study

As mentioned in Chapter 1, the results of this study pertaining to the DOW effect have implications for arbitrage-seeking or abnormal returns seeking investors as well as regulatory and portfolio management. The presence of the DOW effect on the JSE is of significant importance to market participants, regardless of their individual investment mandates. Wealth managers, in endeavours to gain future abnormal returns, would actively seek to know the stock market trends or patterns. Active fund managers will, as best as is possible, seek to beat the market benchmark by achieving the highest possible return given a certain level of risk through optimal capital allocation and diversification. Foreign investors too will seek, in the context of a global equity portfolio, the optimal allocation of capital through improved diversification benefits obtained by including suitably correlated equities exhibiting similar DOW effect patterns.

The findings in this research suggest the prevalence of the DOW effect on the JSE. In order for this anomaly to be in contravention of the laws governing the EMH, they would have to be consistently exploitable, which, by default would mean that DOW effect is predictable. The findings in this research support the existence of the DOW effect that may be adequately exploited without risk. Rather, in conjunction with other predictors of returns, it adds gravitas and provides insight into market movements from a probabilistic standpoint. Descriptive statistics concerning market returns may, in isolation, point towards the existence of a certain anomaly, however coupled with a view of the DOW effect existence in capitalised indices and presiding market conditions, such as varying volatility, it allows for more holistic inferences to be drawn as to the likelihood in direction the market may take.

The knowledge on the existence of the DOW effect across firm size matters to traders and investors on the JSE. As the results have shown that the DOW effect is mostly found in small to medium companies investors are encouraged to invest and trade on small-capitalised companies as they can maximise their returns through following DOW patterns on a daily basis. Portfolio managers and fund managers can also benefit from following the DOW as they can also maximise returns in small-capitalised portfolios and funds. Moreover, investment managers, financial consultant, financial analysts and other stakeholders can make use of the results of this study for advisory purposes.

It may be conjectured that the prevalence of the DOW effect contravenes the laws governing the level of efficiency within the domestic financial markets. The findings in this research point towards having a more holistic view of the changes of the DOW effect over time both in returns and volatility returns. The findings have shown that the DOW effect appear and disappear over time, as such, different investment strategies may be suggested to gain abnormal returns. Given the existence of the DOW effect, the researcher posits that the JSE does not adhere to efficiency levels associated with assumptions of the EMH, whereby market participants stand to gain through fundamental research given certain market patterns.

6.3 Limitations of the Study and Prospects for Future Research

Objectives of the study were achieved; however, there were some limitations on the data characteristics that are known to influence the findings of the DOW effect. Share returns only were utilised for statistical analysis, but investor sentiment and behavioural effects were not considered in the analysis, as they cannot be quantifiable to aid the understanding the resultant force behind the nature of returns used in the study. In addition, transactional costs were not included in the analysis due to the unavailability of the data; this limits the results from showing the accurate picture of stock returns and their volatility. Future research about the DOW effect should investigate whether microstructure-based factors can explain the switches in the daily statistical properties of daily returns along its evolution, and the extent to which abnormal returns can be maximised through following different patterns being detected.

There are psychological factors that led to existence of the DOW effect such as human behaviour that cannot be quantifiable which limits the full understanding of the DOW effect. To add on, GARCH models do not capture those non-quantifiable characteristics of the data. Future studies are recommended to consider better models that have more advantages over the limitations of the GARCH models in order to capture all the characteristics of share returns.

Therefore, this study recommends that future studies should look at the factors that affect stock returns and volatility that can lead to the existence of the DOW effect. There is a need to examine and understand those factors on the size of their impact or effect on returns. That allows investors or any other stakeholders to be knowledgeable on the factors that lead to a certain type of effect (positive or negative). This study was limited to the JSE stock market only but some countries like China had examined the existence of the DOW effect in other markets like foreign exchange markets and bonds market. Further studies are recommended to examine the existence of the DOW effect in other markets that are not stock markets in South African economy.

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APPENDIX 1: ETHICAL CLEARANCE LETTER

APPENDIX 2: TURNITIN REPORT

APPENDIX 3: R CODES

```
rm(list= ls()[!(ls() %in% c(""))]) # clear environment and leave the se-
lected
#if(!is.null(dev.list())) dev.off() # clear all plots
cat("\014")                        # clear console
options(prompt = "R>")             # customize prompt

load(file ="C:/Users/Google Drive/Other/Linah/Linah/allindex.rda")
if(!require(lubridate)){install.packages("lubridate")}
allindex$date = as.Date(allindex$date, origin="1901-01-01")
if(!require(Rcmdr)){install.packages("Rcmdr")}
if(!require(ggplot2)){install.packages("ggplot2")}

# Stationarity plot
myformat=(
      theme(                # Format all the items on the graph
    plot.title = element_text(color="black", size=10, face="bold",hjust =
0.5),
    axis.title.x = element_text(color="black", size=9, face="plain",an-
gle=0),
    axis.text.x = element_text(color="black",size=8,angle=90,vjust = 0.5),
    axis.title.y = element_text(color="black", size=9, face="plain"),
    axis.text.y = element_text(color="black",size=8,angle=0),
    legend.position="top",
    legend.background = element_rect(fill="white",size=0.2,line-
type="solid",colour ="lightblue"),
    legend.title = element_text(colour="black",size=8,face="bold"),
    legend.text = element_text(colour="black",size=8,face="plain")
     ))
ggplot(data = allindex, aes(x=date, y=returns, group = index)) +
  scale_x_date(date_breaks="year",date_labels = "%Y-%m-%d")+
  facet_grid(index~., scales="free")+
  geom_line(aes(color = factor(index)))+
  scale_color_manual(values=c("black","green","red","blue"),
                    name = "INDEX:")+
  labs(title ="" ,x = "Time"
       , y = "Returns"
       )+
  theme_bw()+
  myformat
```

```
########################################################################
#
# LOAD ALL DATA SETS FROM EXCELL AND PREPARE THEM INTO EVIEW FORMAT
#
########################################################################

# Load all the data sets from Excell
rm(list=ls()[!(ls() %in% c())]) # clean environment
cat("\014") # clean console

if(!require(xlsx)){install.packages("xlsx")}
smallindex_a = read.xlsx("C:/Users/user/Google
Drive/MSc/DATA/alldata_xlsx.xlsx",sheetName="small")
save(smallindex_a, file="C:/Users/user/Google Drive/MSc/DATA/smallin-
dex_a.rda")

mediumindex_a = read.xlsx("C:/Users/user/Google
Drive/MSc/DATA/alldata_xlsx.xlsx",sheetName="medium")
save(mediumindex_a, file="C:/Users/user/Google Drive/MSc/DATA/mediumin-
dex_a.rda")

largeindex_a = read.xlsx("C:/Users/user/Google
Drive/MSc/DATA/alldata_xlsx.xlsx",sheetName="large")
save(largeindex_a, file="C:/Users/user/Google Drive/MSc/DATA/largein-
dex_a.rda")

altxindex_a = read.xlsx("C:/Users/user/Google
Drive/MSc/DATA/alldata_xlsx.xlsx",sheetName="altx")
save(altxindex_a, file="C:/Users/user/Google Drive/MSc/DATA/altxin-
dex_a.rda")


########################################################################
#
# NOTE: ALWAYS START FROM HERE (Excel files very slow to open)
#
########################################################################

rm(list=ls()[!(ls() %in% c())]) # clean environment
cat("\014") # clean console
```

```r
# load all data
load(file="C:/Users/user/Google Drive/MSc/DATA/smallindex_a.rda")
load(file="C:/Users/user/Google Drive/MSc/DATA/mediumindex_a.rda")
load(file="C:/Users/user/Google Drive/MSc/DATA/largeindex_a.rda")
load(file="C:/Users/user/Google Drive/MSc/DATA/altxindex_a.rda")

# SMALL -------------------------------------------------------------------
-------------
rm(list=ls()[!(ls() %in% c())]) # clean environment
cat("\014") # clean console

load(file="C:/Users/user/Google Drive/MSc/DATA/smallindex_a.rda")
if(!require(dplyr)){install.packages("dplyr")}
smallindex_b = smallindex_a %>% arrange(date)
smallindex_b$index = rep("small")
smallindex_b$returns = c(NA, diff(log(smallindex_b$price),lag=1))
smallindex_c = smallindex_b[-1,] # drop first row with NA

if(!require(lubridate)){install.packages("lubridate")}
smallindex_c$datenew = as.Date(as.character(smallindex_c$date),format="%Y-
%m-%d")
smallindex_c$date = NULL
setnames(smallindex_c,"datenew","date")
smallindex_c$wkday = format(smallindex_c$date,format="%A") # extract week-
day only
smallindex_c$year = format(smallindex_c$date,format="%Y")  # extract year
only

smallindex_c$mon = ifelse(smallindex_c$wkday=="Monday",1,0)
smallindex_c$tue = ifelse(smallindex_c$wkday=="Tuesday",1,0)
smallindex_c$wed = ifelse(smallindex_c$wkday=="Wednesday",1,0)
smallindex_c$thu = ifelse(smallindex_c$wkday=="Thursday",1,0)
smallindex_c$fri = ifelse(smallindex_c$wkday=="Friday",1,0)

smallindex_d = smallindex_c[,c(2,4,6,5,7:11,1,3)]
smallindex = smallindex_d
save(smallindex, file="C:/Users/user/Google Drive/MSc/DATA/smallindex.rda")

if(!require(xlsx)){install.packages("xlsx")}
write.xlsx(smallindex, file="C:/Users/user/Google Drive/MSc/DATA/smallin-
dex.xlsx", row.names = FALSE)
```

```
# medium ------------------------------------------------------------------
--------------
rm(list=ls()[!(ls() %in% c())]) # clean environment
cat("\014") # clean console

load(file="C:/Users/user/Google Drive/MSc/DATA/mediumindex_a.rda")
if(!require(dplyr)){install.packages("dplyr")}
mediumindex_b = mediumindex_a %>% arrange(date)
mediumindex_b$index = rep("medium")
mediumindex_b$returns = c(NA, diff(log(mediumindex_b$price),lag=1))
mediumindex_c = mediumindex_b[-1,] # drop first row with NA

if(!require(lubridate)){install.packages("lubridate")}
mediumindex_c$datenew = as.Date(as.character(mediumindex_c$date),for-
mat="%Y-%m-%d")
mediumindex_c$date = NULL
setnames(mediumindex_c,"datenew","date")
mediumindex_c$wkday = format(mediumindex_c$date,format="%A") # extract
weekday only
mediumindex_c$year = format(mediumindex_c$date,format="%Y")  # extract year
only

mediumindex_c$mon = ifelse(mediumindex_c$wkday=="Monday",1,0)
mediumindex_c$tue = ifelse(mediumindex_c$wkday=="Tuesday",1,0)
mediumindex_c$wed = ifelse(mediumindex_c$wkday=="Wednesday",1,0)
mediumindex_c$thu = ifelse(mediumindex_c$wkday=="Thursday",1,0)
mediumindex_c$fri = ifelse(mediumindex_c$wkday=="Friday",1,0)

mediumindex_d = mediumindex_c[,c(2,4,6,5,7:11,1,3)]
mediumindex = mediumindex_d
save(mediumindex, file="C:/Users/user/Google Drive/MSc/DATA/mediumin-
dex.rda")

if(!require(xlsx)){install.packages("xlsx")}
write.xlsx(mediumindex, file="C:/Users/user/Google Drive/MSc/DATA/mediumin-
dex.xlsx", row.names = FALSE)


# large -------------------------------------------------------------------
------------
```

```
rm(list=ls()[!(ls() %in% c())]) # clean environment
cat("\014") # clean console

load(file="C:/Users/user/Google Drive/MSc/DATA/largeindex_a.rda")
if(!require(dplyr)){install.packages("dplyr")}
largeindex_b = largeindex_a %>% arrange(date)
largeindex_b$index = rep("large")
largeindex_b$returns = c(NA, diff(log(largeindex_b$price),lag=1))
largeindex_c = largeindex_b[-1,] # drop first row with NA

if(!require(lubridate)){install.packages("lubridate")}
largeindex_c$datenew = as.Date(as.character(largeindex_c$date),format="%Y-
%m-%d")
largeindex_c$date = NULL
setnames(largeindex_c,"datenew","date")
largeindex_c$wkday = format(largeindex_c$date,format="%A") # extract week-
day only
largeindex_c$year = format(largeindex_c$date,format="%Y")  # extract year
only

largeindex_c$mon = ifelse(largeindex_c$wkday=="Monday",1,0)
largeindex_c$tue = ifelse(largeindex_c$wkday=="Tuesday",1,0)
largeindex_c$wed = ifelse(largeindex_c$wkday=="Wednesday",1,0)
largeindex_c$thu = ifelse(largeindex_c$wkday=="Thursday",1,0)
largeindex_c$fri = ifelse(largeindex_c$wkday=="Friday",1,0)

largeindex_d = largeindex_c[,c(2,4,6,5,7:11,1,3)]
largeindex = largeindex_d
save(largeindex, file="C:/Users/user/Google Drive/MSc/DATA/largeindex.rda")

if(!require(xlsx)){install.packages("xlsx")}
write.xlsx(largeindex, file="C:/Users/user/Google Drive/MSc/DATA/largein-
dex.xlsx", row.names = FALSE)

# altx ---------------------------------------------------------------------
-----------
rm(list=ls()[!(ls() %in% c())]) # clean environment
cat("\014") # clean console

load(file="C:/Users/user/Google Drive/MSc/DATA/altxindex_a.rda")
if(!require(dplyr)){install.packages("dplyr")}
```

```
altxindex_b = altxindex_a %>% arrange(date)
altxindex_b$index = rep("altx")
altxindex_b$returns = c(NA, diff(log(altxindex_b$price),lag=1))
altxindex_c = altxindex_b[-1,] # drop first row with NA

if(!require(lubridate)){install.packages("lubridate")}
altxindex_c$datenew = as.Date(as.character(altxindex_c$date),format="%Y-%m-
%d")
altxindex_c$date = NULL
setnames(altxindex_c,"datenew","date")
altxindex_c$wkday = format(altxindex_c$date,format="%A") # extract weekday
only
altxindex_c$year = format(altxindex_c$date,format="%Y")  # extract year
only

altxindex_c$mon = ifelse(altxindex_c$wkday=="Monday",1,0)
altxindex_c$tue = ifelse(altxindex_c$wkday=="Tuesday",1,0)
altxindex_c$wed = ifelse(altxindex_c$wkday=="Wednesday",1,0)
altxindex_c$thu = ifelse(altxindex_c$wkday=="Thursday",1,0)
altxindex_c$fri = ifelse(altxindex_c$wkday=="Friday",1,0)

altxindex_d = altxindex_c[,c(2,4,6,5,7:11,1,3)]
altxindex = altxindex_d
save(altxindex, file="C:/Users/user/Google Drive/MSc/DATA/altxindex.rda")

if(!require(xlsx)){install.packages("xlsx")}
write.xlsx(altxindex, file="C:/Users/user/Google Drive/MSc/DATA/altxin-
dex.xlsx", row.names = FALSE)

#########################################################################
#
# COMBINE ALL PREPARED DATA SETS INTO ONE
#
#########################################################################
rm(list=ls()[!(ls() %in% c())]) # clean environment
cat("\014") # clean console

load(file="C:/Users/user/Google Drive/MSc/DATA/smallindex.rda")
load(file="C:/Users/user/Google Drive/MSc/DATA/mediumindex.rda")
load(file="C:/Users/user/Google Drive/MSc/DATA/largeindex.rda")
load(file="C:/Users/user/Google Drive/MSc/DATA/altxindex.rda")
```

```
allindex = rbind(smallindex,mediumindex,largeindex,altxindex)

allindex$year = as.numeric(allindex$year)

save(allindex, file="C:/Users/user/Google Drive/MSc/DATA/allindex.rda")


########################################################################
#
# STATIONARITY PLOTS
#
########################################################################

rm(list= ls()[!(ls() %in% c(""))]) # clear environment and leave the se-
lected
#if(!is.null(dev.list())) dev.off() # clear all plots
cat("\014")                         # clear console
options(prompt = "R>")              # customize prompt

load(file ="C:/Users/Google Drive/Other/Linah/Linah/allindex.rda")
if(!require(lubridate)){install.packages("lubridate")}
allindex$date = as.Date(allindex$date, origin="1901-01-01")
if(!require(Rcmdr)){install.packages("Rcmdr")}
if(!require(ggplot2)){install.packages("ggplot2")}

# Stationarity plot
myformat=(
      theme(                  # Format all the items on the graph
    plot.title = element_text(color="black", size=10, face="bold",hjust =
0.5),
    axis.title.x = element_text(color="black", size=9, face="plain",an-
gle=0),
    axis.text.x = element_text(color="black",size=8,angle=90,vjust = 0.5),
    axis.title.y = element_text(color="black", size=9, face="plain"),
    axis.text.y = element_text(color="black",size=8,angle=0),
    legend.position="top",
    legend.background = element_rect(fill="white",size=0.2,line-
type="solid",colour ="lightblue"),
    legend.title = element_text(colour="black",size=8,face="bold"),
    legend.text = element_text(colour="black",size=8,face="plain")
```

```
    ))
ggplot(data = allindex, aes(x=date, y=returns, group = index)) +
  scale_x_date(date_breaks="year",date_labels = "%Y-%m-%d")+
  facet_grid(index~., scales="free")+
  geom_line(aes(color = factor(index)))+
  scale_color_manual(values=c("black","green","red","blue"),
                     name = "INDEX:")+
  labs(title ="" ,x = "Time"
       , y = "Returns"
       )+
  theme_bw()+
  myformat




#######################################################################
#
# ROLLING WINDOWS: OPEN ALL COMBINED DATA AND SELECT ANY SUBSET NEEDED
#
#######################################################################
rm(list=ls()[!(ls() %in% c())]) # clean environment
cat("\014") # clean console

# Load the main data (all indices combined)
load(file="C:/Users/user/Google Drive/MSc/DATA/allindex.rda")

#-----------------------------------------------------------------------
# Select one index data
myindex = subset(allindex, index=="large")
 #^^^                                  #^^^
if(!require(xlsx)){install.packages("xlsx")}
write.xlsx(myindex, file="C:/Users/user/Google Drive/MSc/DATA/myin-
dex.xlsx", row.names = FALSE)
            #^^^                                                  #^^^
#-----------------------------------------------------------------------

#-----------------------------------------------------------------------
# Select one index data and specific window
small = subset(allindex, index=="small") # select the index first
```

```
if(!require(Hmisc)){install.packages("Hmisc")}
describe(small$year)    # view the years in the index
        # ^^^^<$
sma_2017_19= subset(allindex, index=="small" & year>=2017 & year<=2019)
 #^^^                                #^^^

describe(sma_2017_19$year)
describe(sma_2017_19$index)

if(!require(xlsx)){install.packages("xlsx")}
write.xlsx(sma_2017_19, file="C:/Users/user/Google
Drive/MSc/DATA/sma_2017_19.xlsx", row.names = FALSE)
                #^^^
#^^^
#-------------------------------------------------------------------------




########################################################################
#
# OPEN ALL COMBINED DATA AND SELECT ANY SUBSET NEEDED
#
########################################################################
rm(list=ls()[!(ls() %in% c())]) # clean environment
cat("\014") # clean console

# Load the main data (all indices combined)
load(file="C:/Users/user/Google Drive/MSc/DATA/allindex.rda")

#-------------------------------------------------------------------------
# Select one index data
altx = subset(allindex, index=="altx")
 #^^^                                #^^^
if(!require(xlsx)){install.packages("xlsx")}
write.xlsx(altx, file="C:/Users/user/Google Drive/MSc/DATA/altx.xlsx",
row.names = FALSE)
            #^^^                                              #^^^
#-------------------------------------------------------------------------
```

```r
#--------------------------------------------------------------------------
# Select one index data and specific window
altx = subset(allindex, index=="altx") # select the index first

if(!require(Hmisc)){install.packages("Hmisc")}
describe(altx 2006-8)    # view the years in the index
        # ^^^^<$
altx 2006-8 = subset(allindex, index=="altx 2006-8" & year>=2006 &
year<=2008)
 #^^^                              #^^^

describe(alt_2006_8$year)
describe(alt_2006_8$index)

if(!require(xlsx)){install.packages("xlsx")}
write.xlsx(alt_2006_8, file="C:/Users/user/Google
Drive/MSc/DATA/alt_2006_8.xlsx", row.names = FALSE)
                #^^^
#^^^
#--------------------------------------------------------------------------
```