# *The Day-of-the-Week Effect on Stock Market Returns Volatility: South African Context*


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# DECLARATION

I, Niyoshaka Stanley Lameck, declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration in the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

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Niyoshaka N. S. Lameck

On the ……………………day of ………………2015.

# ABSTRACT

Volatility of returns is an important parameter in reaching financial decisions among investors. As such, a concise understanding of returns volatility trends could help in predicting stock price.

A study was undertaken to examine the existence of the variations in volatility of stock returns by the day of the week referred to as the day-of-the-week effect on returns volatility and how the effect has evolved during three five-year sub-periods on the Johannesburg Securities Exchange (JSE). Data for the JSE Top 40, Mid Cap and Small Cap indices from 1996 to 2010 were used for the study. The variations of mean returns and returns volatility were examined.

Monday was observed to be highest mean returns day for the JSE Top 40 and Friday for JSE Mid Cap and JSE Small Cap. Tuesday was the lowest mean returns day for all the three indices. Monday and Thursday's day-of-the-week effect on returns was detected for the JSE Top 40 and on Thursday and Friday for the JSE Mid Cap and JSE Small Cap at the 1% confidence level. The Monday, Wednesday, Thursday and Friday day-of-the-week effects are present for JSE Mid Cap and the Wednesday day-of-the-week effect for the JSE Small Cap at 5% confidence level.

Thursday has the highest returns volatility for the JSE Top 40. The JSE Mid Cap and JSE Small Cap have their highest returns volatility on Wednesday and Monday respectively. For all the indices, Fridays have the lowest returns volatility.

The presence of the day-of-the-week effect in returns volatility was observed for the JSE Small Cap. The results do not show a strong effect in the JSE Top 40 returns volatility, whereas the effect is insignificant for the JSE Mid Cap index.

For the 1996 to 2000, 2001 to 2005 and 2006 to 2010 sub-periods, their respective highest mean returns day are Thursday, Tuesday and Monday and lowest mean returns days are Monday, Thursday and Friday. The day-of-the-week effect in mean returns was detected for Wednesday and Friday at 1% for the 2001 to 2005 sub-period and on Tuesday, Wednesday and Friday at 5% for 2006 to

2010. The day-of-the-week effect was not detected in the 1996 to 2000 sub-period in mean returns.

The highest and lowest returns volatility days for 1996 to 2000 are Monday and Friday respectively. The respective highest and lowest returns volatility days are Friday and Thursday for 2001 to 2005 and Friday and Monday for 2006 to 2010. For 1996 to 2000, the day-of-the-week effect in returns volatility was only observed on Friday at the 1% confidence level and on Monday and Thursday at the 10% confidence level. For the 2001 to 2005 and 2006 to 2010 sub-periods, the effect was statistically insignificant at the 10%confidence level.

The day-of-the-week effect on returns volatility for JSE Top 40 for the sub-periods studied has shown to disappear on the South African JSE. Given that apart of Friday, the effect for Monday and Thursday for 1996 to 2000 was only significant at the 10% confidence level, this suggests a very weak effect on the two days.

# DEDICATION

This work is dedicated to special people in my life:

My mother, father, sisters and brothers.

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# INTRODUCTION

# Chapter One: Introduction

## 1.1. Purpose of the study

The purpose of this research is to analyse whether the day of the week has an effect on South African stock market returns volatility using three indices, namely Johannesburg Securities Exchange (JSE) Top 40, JSE Mid Cap and JSE Small Cap. The research also investigates whether the effect has evolved, disappeared, weakened or reversed as the South African stock market matures.

## 1.2. Context of the study

For a rational financial decision maker, returns constitute only one part of the decision-making process (Charles, 2010). Another part that must be taken into account when one makes investment decisions is the risk and/or volatility of returns (Charles, 2010). For investors (http://www.retailinvestor.org/risk.html, 2009), the wider swing in asset prices is greatly attached to increased emotions and worries. High asset volatility may result in increased shortfall if the assets have to be sold for cash flow purposes. Higher volatility in assets may present opportunities to buy assets cheaply when these are under-priced and sell them at a premium when they are at the upper end of the volatility range.

The research by Dutt & Humphery-Jenner (2013) highlighted the link between stock return volatility, operating performance, and stock returns, indicating that low volatility stocks earn higher returns than high volatility stocks in emerging markets and developed markets outside of North America. Higher volatility of returns while saving for retirement may result in a wider distribution of possible final portfolio values and when the retiree makes withdrawals, a higher volatility may result in a larger permanent impact on the portfolio's value (http://www.retailinvestor.org/risk.html, 2009). The volatility of daily returns of the JSE Africa Top 40 is indicated in Figure 1.

Volatility is an inevitable market experience mirroring fundamentals, information and market expectation (Gregoriou, 2009). These three elements are closely associated and interact with each other.

It is important to know whether there are variations in volatility of stock returns by the day of the week and whether a high (low) return is associated with a correspondingly high (low) volatility for a given day. If investors can identify a certain pattern in volatility, making investment decisions based on both return- and volatility-based risk becomes easy. For example, investors who do not like to be exposed to high risk may adjust their portfolios by reducing their investments in assets whose volatility is expected to increase on particular days.

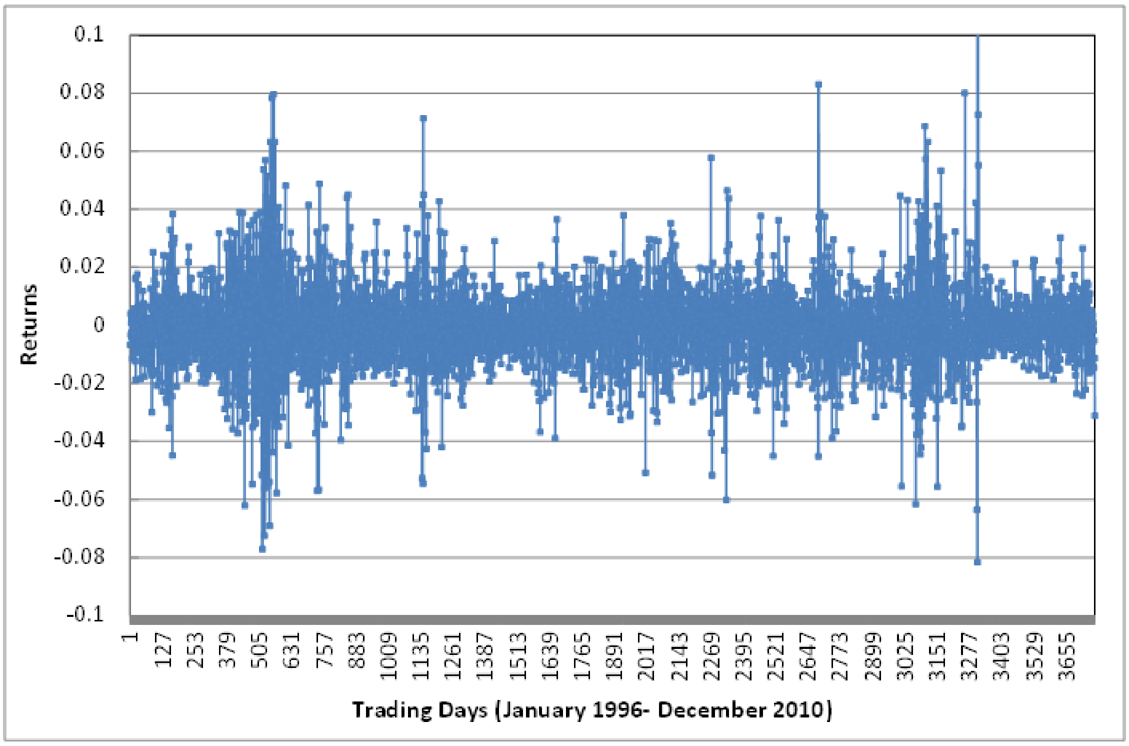


***Figure 1: Daily return for JSE Africa Top 40 Index (January 1996 to December 2010)***

Uncovering certain volatility patterns in returns might also benefit investors in valuation, portfolio optimisation, option pricing, and risk management.

Volatility is thus an important parameter in reaching financial decisions among investors as well as in pricing financial securities.

The assumption of efficient capital markets, which quickly move asset prices to equilibrium, is a major tenet in financial-asset-pricing models (Philpot & Peterson, 2011). Many researchers have conducted empirical studies at different levels of efficiency in markets for various assets and in varied geographic settings. These studies resulted in mixed findings and explanations. The notion of informational efficient markets has such logical and theoretical appeal and, therefore, any test of market efficiency is a dual test of efficiency and the assumed model of returns generation. Researchers often refer to specific persistent and systematic, apparent market inefficiencies as anomalies (Philpot & Peterson, 2011).

Various studies have been conducted to investigate the existence of calendar anomalies in many capital markets across the world.

Calendar anomalies arise from the observation of systematic patterns of security returns around certain calendar points.

Calendar (weekend, day of the week, January, holiday seasons, national elections etc.) anomalies in financial markets in which market returns and stock market volatility are higher during certain calendar periods, and lower during others have widely been studied. The most common calendar anomalies are the January effect and day-of-the-week effect (Berument & Kiymaz, 2001). Others are turn of the month as well as holiday effects (Nawaz & Mirza, 2012).

In the day-of-the-week effect on stock market volatility using the S&P 500 market index study, Berument and Kiymaz (2001) found that the day-of-the-week effect was present in both volatility and return equations. Berument and Kiymaz (2001) observed that the higher and lower returns were on Wednesday and Monday, and the highest and lowest volatility were on Friday and Wednesday.

Studies by Tilica and Oprea, (2014), Diaconasu, Mehdian, & Stoica (2012), Philpot and Peterson (2011), Berument and Kiymaz (2001), Kiymaz and Berument (2003), Chen, Kwok and Rui (2001), and Berument, Coskun and Sahin (2007), indicated that the distribution of stock returns varies according to the day of the week.

Studies have shown that the day-of-the-week effect is not limited to the United States of America (USA) only but varies from one country to another. Kiymaz and Berument (2003) observed that the highest volatility of returns was on Mondays for Germany and Japan, on Fridays for Canada and the USA, and on Thursdays for the United Kingdom. Kiymaz and Berument (2003) also found that the lowest volatility of returns occurs on Mondays for Canada, Tuesdays for Germany, Japan, the United Kingdom, and the USA. The lower trading volumes occur on Mondays and Fridays for Japan, the United Kingdom, and the United States, and the highest trading volume occurs on Tuesdays for each market. The calendar anomalies have also been found in other stock markets/countries such as China (Chen et al., 2001), Turkey (Berument et al., 2007), the USA and Asia-Pacific (Hui, 2005), Romania (Tilica & Oprea, 2014), five stock markets in Southern Asia (Lari, Mardani, & Aghaeiboorkhrili, 2013) and Chittagong Stock Exchange-Bangladesh (Islam & Sultana, 2015). Stock market volatility was also observed around national elections (Białkowski, Gottschalk, & Wisniewski, 2008).

There has been some speculation as to whether seasonal anomalies are a "natural stage" in the evolution of financial markets, whereby the more advanced economies have already passed through on the way to market efficiency while the emerging stock markets are just entering such a stage (Ajayi, Mehdian, & Perry, 2004). However, research still continues to point to the continued existence of the effect of the day of the week on returns and volatility (Philpot & Peterson, 2011).

Of the three levels of market information efficiencies, namely the weak, semi-strong and strong, the calendar anomalies are problematic for weak-form market efficiency (Philpot & Peterson, 2011). The efficient-markets hypothesis implies that asset prices rapidly change in adjustment to information and thus should move in an unpredictable, irregular pattern. If a foreseeable pattern exists, profit-maximising investors would notice the pattern and price the assets in anticipation; when prices reflect the anticipation, the pattern would vanish.

It is argued that (Philpot & Peterson, 2011) apart from the obvious opportunity to speculate on predictable price movement patterns, the existence of calendar effects allows a genuine opportunity for long-term- and regular (e.g. dollar cost averaging) investors to enhance returns. However, it is also counter-argued that given the small magnitude of the effect, the transactional costs and the taxes, the profit opportunities arising from volatility variations among the days of the week vanish and therefore investors cannot benefit from the effect (Philpot & Peterson, 2011). The only potential for profiting from the day-of-the-week effect through trading individual stocks would be through changing the timing of trades that are already planned, such as timing purchases for Mondays and sales for Fridays in the case of a Monday effect (Charles, 2010).

Many potential explanations for the weekend effect have been proposed and investigated (Charles, 2010). These include:

- measurement errors
- delay between trading and settlement in stocks
- specialist-related biases in prices
- spill-over effect from other large markets
- concentration of certain investment decisions
- timing of corporate releases after Friday's close
- reduced institutional trading and greater individual trading on Mondays
- country-specific settlement procedures
- risk-return trade-offs
- daily savings for two weekends a year
- speculative short sales
- new political macroeconomics and transactions costs.

At this point, it should be noted that the above-mentioned explanations are not fully adequate for explaining the phenomenon of the day-of-the-week anomaly. The literature to date does not provide an adequate explanation for this phenomenon (Charles, 2010). Despite the various studies, it remains an area for further research as to what causes these anomalies across calendar periods.

Whereas day-of-the-week anomalies in the USA, Europe and other advanced equity markets have been investigated extensively, the emerging markets have received much less attention.

In the case of South Africa, several attempts have been made by several authors (Coutts & Sheikh, 2002; Heymans, 2005; Mbululu & Chipeta, 2012, Kalidas, Mbululu, & Chipeta, 2013) in trying to understand the South African stock markets and factors that affect them.

In their study of the weekend, January and pre-holiday effects on South African stock markets using dummy regression models to detect any seasonal patterns in returns of the JSE All Gold Index from January 1987 to May 1997, (Coutts & Sheikh, 2002) found no evidence of weekend, January and pre-holiday effect on the returns of the JSE All Gold Index. Despite finding insignificant negative Monday and January returns, (Coutts & Sheikh, 2002) findings were viewed as contradictory to many findings for both developed and emerging markets. Heymans (Heymans, 2005) investigated the existence of the day-of-the-week effect on returns on the JSE using the closing prices for the All Share Index (ALSI). Using parametric, non-parametric and dummy regression variable equations, Heymans identified the presence of the day-of-the-week effect on returns. According to Heymans (2005), mean returns on Thursdays were reported to be higher than on any other day of the week.

Heymans (2005) did not examine the day-of-the-week effect on variations in stock market returns volatility or higher statistical moments. Furthermore, it is also crucial to investigate the existence of this anomaly in returns volatility using other indices to examine if the sizes of companies play roles in the day-of-the-week effects.

Alagidede (2008) studied the day-of-the-week seasonality in African stock markets whilst Alagidede and Panagiotidis (2009) modelled stock returns in Africa's emerging equity markets. Mandimik and Chinzara (2010) studied the risk-return trade-offs and behaviour of volatility on the South African stock market whilst Mbululu and Chipeta (2012) studied the day-of-the-week effect on skewness and kurtosis on the nine listed economic stock market sectors indices of the JSE and found no evidence of the day-of-the-week effect on skewness and kurtosis for eight of the nine JSE stock market sectors.

Despite numerous studies, none of these studies has investigated the presence of the day-of-the-week effect on stock market returns volatility on the JSE.

It is therefore important that the effect of the day of the week on the JSE returns volatility be investigated to establish if it exists and on which days the returns volatility is higher or lower. This could offer valuable findings to investors. Likewise, understanding the South African stock market volatility could provide valuable information for stockholders in the South African stock market.

## 1.3. Problem statement

### *1.3.1. Main problem*

A concise understanding of returns-volatility trends provides an avenue of predicting stock price, which is a crucial component of decision making process for investors. However, the problem is that investors, portfolio managers, risk arbitrageurs and corporate treasurers are unable to accurately predict stocks prices; resulting in ineffectiveness in managing investments against a potential market risks, as well as an inability to create and identify investment opportunities.

The research problem is to determine whether the JSE Securities Exchange exhibits different returns volatility on different days of the week, the “day of the week effect” for the past fifteen (15) years from 1996 to 2010. The analysis examines the JSE Top 40, JSE Mid Cap and JSE Small Cap indices over that period. The research also examines and analyses how the effect of the day of the week on the returns volatility of the South African stock market has evolved during the 1996 to 2000, 2001 to 2005, and 2006 to 2010 sub-periods.

### *1.3.2. Sub-problem 1*

The first sub-problem is to determine whether the day of the week has an effect on the returns volatility of the South African stock market as it has been observed in other stock markets.

#### *1.3.3. Sub-problem 2*

The second sub-problem is to analyse the evolution of the day-of-the-week effect on South African stock market returns volatility during different three five-year sub-periods (1996 to 2000, 2000 to 2005, and 2005 to 2010). The analysis will lead to the determination as to whether the effect has evolved, disappeared, weakened or reversed as the South African stock market efficiency improves as a result of stock market maturing.

## 1.4. Significance of the study

As stock-returns volatility is one of the measures of risk, it is an important parameter for investors, analysts, brokers, dealers and regulators. The excessive volatility may have an adverse impact on the usefulness of stock price as a signal of value of a firm. This research will bridge the information and understanding gap by providing insight into the South African stock market returns volatility among the different days of the week.

The establishment of the existence of the day-of-the-week effect on the returns volatility of the South African stock market may assist in understanding the South African stock market and may be helpful to investors in making investment decisions based on daily risks resulting from expected volatility.

## 1.5. Delimitations of the study

Research in modelling stock volatility has evolved for many years and different scholars have made significant contributions in this area. In this line, different models for financial volatility forecasting and daily stock variability have been developed and used (Li & Hong, 2011).

Thus, it is to be noted that this study will not try to either develop a model for returns volatility or attempt to evaluate the suitability and performance of various models in existence. The study will adopt widely used model(s) based on findings from the literature and will use these models to study the effect of the day of the week on the returns volatility of the stock market.

Despite the many studies conducted to investigate the calendar anomalies, no one single explanation seems to have been generally accepted although many have intuitive appeal (Philpot & Peterson, 2011). Many potential explanations for the weekend effect have been proposed and investigated (Charles, 2010). Still, the anomalies remain unexplained as to what causes them to exist across calendar periods. This study will neither focus on studying the underlying explanations for such anomalies nor reasons behind such anomalies if observed in the South African stock market.

Given the time constraints, the study will focus on the JSE Top 40, the JSE Mid Cap and the JSE Small Cap indices as representative of companies listed on the JSE rather than study individual companies or sectors. The daily stock trade data from January 1996 to December 2010 will be analysed.

## 1.6. Definition of terms

"Volatility" can be defined as the variation, dispersion, or deviation of a financial instrument from their mean. Volatility measures the extent of price movement in an option, stock, future or any market.

"Heteroskedasticity" is a condition that exists when variance of the error term does not appear to be constant over a range of predictor variables (Hair, Black, Babin, & Anderson, 2010).

"Stochastic process" is a mechanism that generates random observation

"Normality" refers to the degree to which the distribution of the sample data corresponds to normal distribution (Hair et al., 2010).

## 1.7. Assumptions

The following underlying assumptions were made during this study:

- The data for the study was assumed to be credible, as it is based on the JSE listing database

- The model used to model volatility in other stock markets could also be used to model returns volatility on the South African stock market

- It was assumed that the JSE Top 40, the JSE Mid Cap and the JSE Small Cap can represent JSE-listed companies. The results obtained using these indices would therefore give an indication of the effect of the day of the week and also indicate the variation among the different-sized companies

- It was assumed that the JSE Top 40 would mainly constitute large firms and that the JSE Small Cap would represent smaller firms

- On public holidays, no trading took place. This left the stock price unchanged. Given the numbers of public days per year, removing the entire rows for missing data observations could have resulted in reducing the number of observations by more than one-third. The treatment of public holidays then assumed that the public holiday's closing stock prices were equal to their previous trading day's closing prices – thus zero returns.

# CHAPTER TWO:

# LITERATURE REVIEW

## 2.1. Introduction

The first section of the literature survey introduces various approaches used in defining volatility and estimating returns, as well as different models used in modelling returns volatility.

Thereafter achievements by different authors in studying the calendar anomalies in stock market returns and returns volatility are reviewed. This is followed by an investigation of the literature on the evolution of the day-of-the-week effects. The hypotheses arising from literature survey and sub-problems are then presented, followed by concluding remarks on the literature review.

## 2.2. Background Discussion

In an ideal market, pricing an option or stock requires inputs that could include current stock price, the strike price, time to expiry, risk-free interest rate, dividends and volatility (Black & Scholes, 1973). The current stock price, the strike price and time to expiry are well known from the outset, while the risk-free interest rate, dividends and volatility would need to be estimated.

The influence of changes in interest rate to option or stock price is believed to be very minimal compared to volatility, especially during low interest-rate periods. The dividend risk can be minimised through good analysis and research, according to which the future dividends that will be paid during the coming period can be estimated quite accurately (Kotzé, 2005). It then remains that volatility is the most important of the three parameters. The importance of understanding volatility was highlighted by Black and Scholes (1973) in their pricing model for options and corporate liabilities. It is argued that an expected increase in volatility increases the risk of holding the stock (Zhou & Zhou, 2005).

“Volatility” can be defined as the variation, dispersion, or deviation of a financial instrument from their mean (Kotzé, 2005). Volatility measures the extent of price movement in an option, stock, future or any market. The most common measure of dispersion is the standard deviation of a random variable. The larger the value of volatility would indicate fluctuation in returns in a wider range-large risk (Kotzé, 2005).

Traditionally (Li & Hong, 2011), volatility was assumed to be constant and was estimated as the sample standard deviation of daily returns for a period (based on the closing prices). However, it is now well known that volatility is time varying. This fact led to uncovering and categorising volatilities into historical, implied (stochastic) and realised volatilities. The volatility estimated as standard deviations of daily returns is referred to as “historical volatility” (Li & Hong, 2011). In contrast, implied volatility is the volatility of the underlying asset price that is implicit in the market price of an option according to a particular model (Kotzé, 2005).

Implied volatilities should be viewed differently from stochastic volatilities even though they both forecast the volatility of the underlying asset over the life of the option (Kotzé, 2005). The two forecasts differ because they use different data and different models. Implied methods use current data on market prices of options, so the implied volatility contains all the forward expectations of investors about the likely future price path of the underlying.

The realised volatility on the other hand is the historical volatility calculated looking ‘backward’ when an option has expired.

Two different approaches are commonly used to measure and determine volatility (Balakrishnan, 2010). One uses the log return variances where daily returns are computed as the natural logarithmic first difference of the daily closing price as shown in Equation 1.

$$\boldsymbol{R_{t=}}\frac{\boldsymbol{ln(P_t)}}{\boldsymbol{ln(P_{t-1})}} \qquad (1)$$

Pt represents the stock price at the end of the time interval and Rt is a drawing from a normal distribution with time-varying volatility, i.e. $R_t = N(0, h_t^2)$.

The second approach uses the log range variances computed using the high- and low prices during the day. The volatility in this approach can be estimated using the PARK daily volatility estimator developed by Parkinson (1980), which is given in Equation 2.

$$\boldsymbol{h^2_{PARKt}} = \frac{[\boldsymbol{ln}(\boldsymbol{H_t}) - \boldsymbol{ln}(\boldsymbol{L_t})]^2}{\boldsymbol{4 * ln2}} \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \quad 2$$

An alternative to PARK daily volatility estimator was presented by Graman and Krass (1980), who claimed it to be more efficient than that of Parkinson (1980) and is given in Equation 3. The equation advocated by Graman and Krass (1980) make use of both log range and log difference of daily closing price.

$$\boldsymbol{h^2_{(GK)t}} = \boldsymbol{0.5}\left[\boldsymbol{ln}\left(\frac{\boldsymbol{H_t}}{\boldsymbol{L_t}}\right)\right]^{\boldsymbol{2}} - \boldsymbol{0.9}\left[\boldsymbol{ln}\left(\frac{\boldsymbol{P_t}}{\boldsymbol{P_{t-1}}}\right)\right]^{\boldsymbol{2}} \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \quad 3$$

Most studies (Berument and Kiymaz (2001); Kiymaz and Berument (2003); Chen, Kwok and Rui 2001; and Berument, Coskun and Sahin (2007)) have invariably used the log return variances approach to model volatility.

However, Alizadeh, Brandt and Diebolf (2002) noted the log range as being a better measure of volatility compared to log absolute returns. Alizadeh et al. (2002) contend that the log range estimation superiority lies in that the variance of the measurement errors associated with the daily log range is far less than the variance of the measurement errors associated with daily log absolute or squared returns because of the intraday sample path information contained in the range. Second, the log range is very well approximated as Gaussian.

For instance, on a given day, the price of an asset fluctuates substantially throughout the day but its closing price happens to be very close to the previous closing price (Alizadeh, Brandt, & Diebolf, 2002). If one uses the log return of the inter-daily close price, the value will be low despite the large intra-daily price fluctuations. The log range, using the highest and lowest values, reflects more precise price fluctuations and can indicate that the volatility for the day is high.

Parkinson (1980) demonstrated on purely statistical grounds that volatility measures which incorporated high-and low prices are more efficient than returns-based volatility estimator (Fiess & MacDonald, 2002).

However, the argument of log range being superior to log returns overlooks the fact that the log range ignores the direction of the stock price. One must note that the use of daily high and low will always be positive; if the opening stock price is higher than the closing price, the movement direction can never be captured in the log range data.

Despite the acclaimed advantages of the log range, the log range-based volatility estimators have not attracted enough attention in the estimation and forecasting of volatility. Li and Hong (2011) indicate that the less attention could be due to long range based volatility estimators poor performance in empirical studies. Chou (2005) asserted that the fundamental reason that log range has not received much attention is because it cannot adequately capture the dynamics of volatilities.

### *2.2.1 Returns and Volatility Modelling*

Various studies have been carried out to establish and determine the most descriptive models of return generating processes (Alizadeh, Brandt, & Diebold, 2002; Black & Scholes, 1973; Bollerslev, 1986; Engle, 1982; Fukushima, 2011; Parkinson, 1980) in stock and exchange rate time series data.

#### *2.2.1.1 Returns Modelling*

Most studies investigating the day-of-the-week effect in mean returns employ the standard Ordinary Least Square (OLS) methodology by regressing returns on five daily dummy variables as (Kiymaz & Berument, 2003) shown in equation 4.

$$\boldsymbol{R_t = \alpha_0 + \alpha_M M_t + \alpha_T T_t + \alpha_H H_t + \alpha_F F_t + \sum_{i=1}^{n} \alpha_i R_{t-i} + \varepsilon_t} \text{..................} 4$$

Where $R_t$ represents return on a selected index, $M_t$, $T_t$, $H_t$ and $F_t$ are dummy variables for Monday, Tuesday, Thursday and Friday respectively at time t. In order to circumvent the dummy variable trap, the dummy variable for Wednesday was excluded; hence each dummy variable coefficient was interpreted relative to return excess of that of Wednesday. The lag values of the return variables are included in order to eliminate the possibility of having autocorrelation errors. Equation 4 assumes a constant variance. This may result in inefficient estimations in case the variance varies with time. To allow variances of errors to be time dependant, a conditional heteroskedasticity that captures time variation in stock returns, the error term with mean of zero and a changing variance of $h_t^2[\varepsilon_t \sim (0, h_t^2)]$ was also included.

Long and Ervin (2000) also showed that for non-constant variance, the heteroscedasticity consistent covariance matrix, hereafter HCCM, can provide a consistent estimate of the covariance of the slope coefficients in the presence of heteroscedasticity. Long and Ervin (2000) conclude that if the sample is less than 250, the form of HCCM known as HC3 should be used; when the sample is 500 or larger, other versions of HCCM can be used.

#### *2.2.1.2 Volatility Modelling*

The financial time series data exhibit fat tails (i.e. they exhibit excess kurtosis; indicating peaked-ness and taller than normal distribution), volatility clustering (i.e. large movements followed by further large movements), leverage effect in which price movements are negatively correlated with volatility, long memory and co-movement in volatility (Gregoriou, 2009) patterns, which are crucial for correct model specification, estimation and forecasting.

These observations about volatility have led many researchers to focus on the cause of these stylised facts. To get reliable forecasts of future volatilities, it is crucial to account for the stylised facts.

Generally, there are three approaches to volatility modelling (Balakrishnan, 2010) viz GARCH family of model, Stochastic volatility models, and Realised volatility approaches.

#### 2.2.1.2.1 GARCH family of models

Engle (1982) developed an autoregressive conditional heteroskedasticity (ARCH) model, which tried to address the issue of volatility clustering and the origin of the tail behaviour that were not explained in the OLS/ARMA models.

The ARCH model allowed the forecasted variances to change with squared lagged values of error terms from the previous period (Equation 5)

$$\boldsymbol{h_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j\, \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}} \quad \text{.......} 5$$

$\alpha_0$ measures the extent to which volatility shock today feeds into tomorrow's volatility and represents the short-run persistence of shocks on return variance and $\beta_j$ is the contribution of older shocks to the long-run persistence (for j=1…..q).

The ARCH model was followed by the generalised autoregressive conditional heteroskedasticity (GARCH) model which was developed by Bollerslev (1986) as an extension of the ARCH process in order to allow for conditional variance as a function of lagged values of both the $h_t^2$ and $\varepsilon_t^2$ (Equation 6).

$$\boldsymbol{h_t^2 = \alpha_0 + \sum_{j=1}^{q} \beta_j h_{t-j}^2 + \sum_{j=1}^{q} \alpha_j\, \varepsilon_{t-j}^2} \quad \text{.......} 6$$

In order to satisfy the non-explosiveness of the conditional variances, Equation 6 requires that $\sum_{j=1}^{q} \beta_j h_{t-j}^2 + \sum_{j=1}^{r} \alpha_j\, \varepsilon_{t-j}^2 < 1$ and $\beta_j$, $\alpha_j$and $\alpha_0$ are positive in order to satisfy the non-negativity of conditional variances.

Hence, time-varying variance can be modelled using Equation 6 where volatility is measured by conditional variance $h_t$. When the constant term of the conditional variance is allowed to change for each day of the week, Equation 6 becomes:

$$\boldsymbol{h_t^2 = \alpha_0 + \alpha_M M_t + \alpha_T T_t + \alpha_H H_t + \alpha_F F_t + \sum_{j=1}^{q} \beta_j h_{t-j}^2 + \sum_{j=1}^{q} \alpha_j\, \varepsilon_{t-j}^2} 7 \qquad \text{8}$$

Where $h_t^2$ represents lagged conditional variance on selected index, $M_t$, $T_t$, $H_t$ and $F_t$ are dummy variables for Monday, Tuesday, Thursday and Friday respectively at time t. As in equation 4, dummy variable for Wednesday was excluded in order to circumvent the dummy variable trap. Each dummy variable coefficient was interpreted relative to variance excess of that of Wednesday.

The maximising of the Likelihood Estimation (QMLE) (Equation 8) method introduced by Bollerslev and Wooldridge (1992) can then be used for parameter estimation.

$$\boldsymbol{L = -\frac{T}{2} log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}(h_t) - \frac{1}{2}\sum_{t=1}^{T}\frac{\varepsilon_t^2}{h_t}} \qquad \text{9}$$

Where, L is quasi log-likelihood and T is observable random vector same as q in equation 5.

The strength of the GARCH model lies in its flexible adaptation of the dynamics of volatilities and its ease of estimation when compared to the other models.

Li and Hong (2011) argued that the GARCH model is a returns-based model, which is constructed with the data of closing prices. Hence, though the GARCH model is a useful tool to model changing variance in time series, and provides acceptable forecasting performance, it might neglect the important intraday information of the price movement. For example, when today's closing price equals the last day's closing price, the price return will be zero, but the price variation during the day might be turbulent. However, the returns-based GARCH model cannot catch it. Using the intraday GARCH, some studies try to remedy the limit of the traditional GARCH. An alternative way to model the intraday price variation may be the adoption of the price range instead.

Subsequently, different GARCH family models [GARCH (TARCH), GARCH (EGARCH), GARCH (FIGARCH) and GARCH (CGARCH)] were developed in trying to address some shortcomings of the (Bollerslev, 1986) GARCH model

(Gregoriou, 2009). Within these GARCH family models, changes in variability are related to, or predicted by, recent past values of the observed series.

#### 2.2.1.2.2 Realised Volatility

The advent of high-frequency financial data such as transaction-by-transaction data of stock markets makes quadratic variations of intraday returns a viable alternative to modelling volatility (Balakrishnan, 2010). Using the addictive property of log returns, the daily returns are a temporal aggregation of intraday returns; i.e.

$$R_t = \sum_{i=1}^{n} R_{m,i,t} \quad \text{.......} \quad 10$$

where $m$ denotes the intraday times interval measured in minutes, $R_{m,i,t}$ is the $i^{th}$ $m$-minutes log return in date $t$ and $n$ is the total number of $m$-minutes returns in date $t$. The volatility of $R_t$ is given by:

$$\operatorname{var}(R_t \mathrm{I} F_{t-1}) = \sum_{i=1}^{n} \operatorname{var}(R_{m,i,t} \mathrm{I} F_{t-1}) + 2\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \operatorname{cov}(R_{m,i,t}, R_{m,j,t} \mathrm{I} F_{t-1}) \quad \text{.......} \quad 11$$

Under some general conditions, the volatility in Equation 11 can be estimated directly from the intraday log returns.

## 2.3. Stock Market Returns Volatility

Different scholars across the world have carried out numerous studies to investigate the existence of calendar anomalies in capital markets.

Weekend (Brusa et al., 2011), day of the week (Alagidede, 2008; Berument et al., 2007; Berument & Kiymaz, 2001; Charles, 2010; Chen et al., 2001; Kalidas, Mbululu, & Chipeta, 2013; Tilica & Oprea, 2014), holiday seasons (Picou, 2006), and national elections (Białkowski et al., 2008) and Islamic calendar (Halari, Tantisantiwong, Power, & Helliard, 2015) effects at which market returns and stock market volatility are higher during certain calendar periods and lower on others and have widely been studied. These investigations have covered equity, foreign exchange, and the T-bill markets.

Study findings have shown that the calendar effects are present in both the returns and the returns volatility equations. Studies by Philpot and Peterson (2011), Charles (2010), Berument, Coskun and Sahin (2007), Kiymaz and Berument (2003), Berument and Kiymaz (2001),and Chen, Kwok and Rui (2001), have indicated that the distribution of stock returns varies according to the day of the week.

Nawaz & Mirza (2012) reviewed various calender anomalies that were observed over time in different stock market around the globe. Nawaz & Mirza (2012) noted that, initially, Friday returns were larger than the returns on any other day of the week, and even Monday represented negative returns. However, as the trading pattern changed and more institutional investors got involved in trading, Monday returns became positive and were even higher than the Friday returns.

Philpot and Peterson (2011) conducted a review of relevant recent research on the weekend effect. Philpot and Peterson (2011) categorised the weekend effect review into early work, work through 2003, and post-2003 work.

In the early work review, Philpot and Peterson (2011) indicated that in 1973, Cross was among the first to document stock returns regularities as a function of day of the week. Another early study indicated by Philpot and Peterson (2011) on the weekend effect on stock price was that conducted by French in 1980.

In their day-of-the-week effect on stock market volatility using S&P 500 market index study, Berument and Kiymaz (2001) found that the day-of-the-week effect was present in both returns volatility and returns equations. Berument and Kiymaz (2001) observed that the higher and lower returns were on Wednesday and Monday and the highest and lowest returns volatility were on Friday and Wednesday.

Studies have shown that the day-of-the-week effect is not limited to USA and varies among different countries. Kiymaz and Berument (2003) observed that the highest volatility of returns were on Mondays for Germany and Japan, on Fridays for Canada and the United States, and on Thursdays for the United Kingdom. Kiymaz and Berument (2003) found that the lowest volatility of returns occurs on Mondays for Canada, Tuesdays for Germany, Japan, the United Kingdom, and the United States.

In Lari et al. (2013)'s  day of the week effect, annual returns and volatility of five stock markets in Southeast of Asia, their results of the Kruskal-Wallis test showed the presence of the day of the week effect only in Indonesia and other stock returns including Malaysia, Philippine; Singapore and Thailand do not provide the existence of the daily effect. Lari et al. (2013) found that all of five stock return indexes decreased significantly in last month of 2008 then they increased between beginning of 2009 and 2012. The changes in annual closing values of the indexes indicate that in general, the markets seem to gain and lose simultaneously. However Indonesia experienced the greatest percentage increase in this period, Malaysia experienced the lowest increase between other markets. Generally, all of the stock markets in their study shown growth after a decline in the last months of 2008.

Charles (2010) conducted a study to evaluate whether asymmetry influences the day-of-the-week effect on volatility using daily closing prices of five international indices; i.e. CAC 40 (France), DAX 30 (Germany), DJIA (Brusa et al.), FTSE (Fukushima), and NIKKEI 225 (Japan). Charles (2010) found that the average daily returns are positive for all indices except the NIKKEI 225, for which the average daily returns were negative. The lowest variance is displayed on Fridays for CAC 40, DAX 30 and NIKKEI 225.DJIA and FTSE 100 indices display the lowest variance on Wednesday. The highest average returns are observed on Mondays for the DJIA; on Thursdays for CAC 40 and NIKKEI 225 and on Fridays for DAX 30 and FTSE 100. The lowest average returns are on Mondays for CAC 40, FTSE 100 and NIKKEI 225 with a negative sign; on Tuesdays for DAX 30 with a positive sign and on Thursdays for DJIA with a negative sign.

The calendar anomalies have also been found in other stock market/countries such as China (Chen et al., 2001), Turkey (Berument et al., 2007), and US and Asia-Pacific (Hui, 2005), Romania (Tilica & Oprea, 2014), five stock markets in Southern Asia (Lari et al., 2013) and Chittagong Stock Exchange-Bangladesh (Islam & Sultana, 2015). Stock market volatilities were also observed around national elections (Białkowski et al., 2008).

Despite the studies, it remains unexplained as to what causes these anomalies across calendar periods. Many potential explanations for the weekend effect have been proposed and investigated (Charles, 2010). At this point, it should be noted that the explanations given have not adequately explained the phenomenon of the day-of-the-week anomaly. To date, the literature does not provide an adequate explanation for this phenomenon (Charles, 2010).

## 2.4. Variation of the Day-of-the-Week Effect During Different Sub-Periods

Different assertions have been made suggesting the disappearance of the day-of-the-week effect with time. Kalidas et al.,(2013) studied the changing patterns In the day of the week effects In African stock markets in attempt to understand the movements and patterns that investors face. Splitting the daily index data for South Africa, Zambia, Botswana, Nigeria, and Morocco into post and pre-financial crisis for the period of 2004 to 2012, with exception of South Africa, the Authors observed significant changes in patterns over the time for these countries. However, the duration of 2004-2012 cast doubt as to whether the duration studied is long enough to deduce the changing patterns. Kohers, Kohers, Pandey and Kohers (2004) argued that because of improvements in market efficiency over time, the day-of-the-week effect may have disappeared in more recent years. Using both parametric and nonparametric statistical tests, Kohers, Kohers, Pandey and Kohers (2004) examined the evolution of the day-of-the-week seasonality for the largest developed equity markets over the past 22 years. Their results indicated that while the day-of-the-week effect was clearly prevalent in the vast majority of developed markets during the 1980s, it appears to have faded away starting in the 1990s. These findings imply that increases in market efficiency over long time periods may erode the effects of certain anomalies such as the day-of-the-week effect.

Berument and Kiymaz (2001) investigated the day-of-the-week effect in stock market volatility in sub-periods. Their results indicated that the pre- and post-1987 periods reinforce their findings that the volatility patterns across the days of the week are statistically different from each other. In summary, Berument and Kiymaz (2001) detected the day-of-the-week effect on both returns equation and the returns volatility (conditional variance) equations.

Steeley (2001) studied seasonality and the disappearance of the weekend effect in the UK stock market. Steeley (2001) showed that the weekend effect in the UK equity market had disappeared during the 1990s. However, by partitioning the returns data on the basis of market direction, Steeley (2001) found that negative returns on Monday and Friday were significantly different from their mid-week counterparts.

Kohers et al. (2004) applied the day-of-the-week effect to a number of stock indices including US large caps and small caps as well as UK and Japanese indices. These authors found strong evidence of a Monday effect in many cases under this stronger criterion. The effect has reversed or weakened in the Dow Jones and S&P 500 indices post 1987, but it is still strong in more broadly based indices like the NASDAQ, the Russell 2000 and the CRSP. Consequently, the debate on the existence of seasonal patterns on returns remained open.

Baker, Rahman and Saadi (2008) argued that some limited evidence exists on the fragility of the reported evidence of the day-of-the-week effect. For instance, using highly sophisticated procedures, Baker, Rahman and Saadi (2008) contend that in 1989 and 1991, Connolly (1989, 1991) found that the reported evidence of the Monday effect was weak for the U.S. stock market. Baker, Rahman and Saadi (2008) further argue that, in fact, Connolly showed that the day-of the-week effect reported in earlier studies disappears after adjusting the t-critical values for sample size with a Bayesian approach.

Pettengill (1989) seeking to document the weekend effect in US stock prices, noted and explored the shift of Monday returns to positive (a reverse weekend effect) and a movement of effects to other days.

Other researchers have suggested that the effect of the week observation was because of poor statistical means to adequately detect the analytical error.

Despite literature indicating various studies carried out to investigate the disappearance, weakening and/or reversal of the effect, most researchers studied the effect on returns. Not much information related to the disappearance, weakening and/or reversal of the effect on returns volatility.

## 2.5. Hypothesis

The hypotheses are built based on the sub-problems stated in 1.3.2 and 1.3.3

### *2.5.1. First Hypothesis*

The first hypothesis (Section 1.3.2) is built from Section 2.3 where it has been observed that in developed and emerging stock markets the day-of-the-week has been shown to have an effect on returns volatility on the stock market. It has also been learnt that the day-of-the-week effect is not constant (i.e. the trend in the effect is not the same) among the different stock markets.

**Null Hypothesis**

There is no significant difference in returns volatility in stock market returns among the days of the week in the South African stock market i.e.

$$\boldsymbol{H_0}: \boldsymbol{h^2_{Monday}} = \boldsymbol{h^2_{Tuesday}} = \boldsymbol{h^2_{Wednesday}} = \boldsymbol{h^2_{Thursday}} = \boldsymbol{h^2_{Friday}} \text{ ............. } 12$$

Where $H_0$ is a null hypothesis and $h^2$ are the GARCH model coefficients of conditional variance in returns volatility for Monday to Friday

**Alternative Hypothesis**

The alternative hypothesis is that there is significant difference in stock market returns volatility among the days of the week in the South African stock market i.e.

$$\boldsymbol{H_1}: \boldsymbol{h^2_{Monday}} \neq \boldsymbol{h^2_{Tuesday}} \neq \boldsymbol{h^2_{Wednesday}} \neq \boldsymbol{h^2_{Thursday}} \neq \boldsymbol{h^2_{Friday}} \text{ ............. } 13$$

$H_1$ being an alternative hypothesis

### *2.5.2. Second Hypothesis*

From Section 2.4, despite some suggestions and claims that the effect of the day of the week on returns volatility of the stock market is disappearing and weakening as a result of improvement in market efficiency and maturity, it is apparent that the effect still exists and has not been shown to disappear or weaken as claimed by a few authors.

**Null Hypothesis**

The day-of-the-week effect on returns volatility has disappeared in the South African stock market i.e.

$$\boldsymbol{H_0}: \left[\left|\boldsymbol{h^2_{SPi=1}}\right| > \left|\boldsymbol{h^2_{SPi=2}}\right| > \left|\boldsymbol{h^2_{SPi=3}}\right|\right]^{\boldsymbol{5}}_{\boldsymbol{i=1}} \text{ ................................................ } 14$$

Where $h_{SPi}^{2}$ are the GARCH model coefficients of conditional variance in returns volatility for 1996 to 2000, 2000 to 2005 and 2005 to 2010 for Monday to Friday.

**Alternative Hypothesis**

The alternative hypothesis is that the day-of-the-week effect on returns volatility has not disappeared in the South African stock market i.e.

$$\boldsymbol{H_1}: \left[ \left| \boldsymbol{h_{SP1}^2} \right| < \left| \boldsymbol{h_{SP2}^2} \right| < \left| \boldsymbol{h_{SP3}^2} \right| \right]_{\boldsymbol{i=1}}^{\boldsymbol{5}} \quad \text{......} \quad 15$$

## 2.6. Conclusion of Literature Review

The literature survey reviewed different researches on the day-of-the-week effect on stock market returns volatility and the various approaches used for their estimations. From the literature survey, it is apparent that the log returns provides a returns measure that can be used in returns-volatility modelling.

Different volatility models were reviewed. Among them are the GARCH family models, stochastic volatility model and realised volatility model.

It has been observed that the main argument against GARCH inefficiency is that the conditional distribution of log returns or squared return is far from Gaussian. It is argued (Alizadeh, Brandt, & Diebolf, 2002) that the Gaussian quasi-maximum likelihood estimation with these traditional volatility proxies is highly inefficient and often evenly biased in finite sample. Alizadeh et al. (2002) contended that the conditional normality assumption for log returns fail.

The critics of the GARCH model argue that the distribution of log range is very close to normal, which makes it attractive for use in the Gassian QMLE models.

The literature review has indicated that most applications of the GARCH (p,q) model use low orders for the lag lengths p an q, and small GARCH (1,1) is generally found to be most appropriate for forecasting stock returns.

The GARCH (1,1) model has emerged as a workhorse for modelling inter-daily volatility clustering in financial markets, as it tends to provide a simple approximation of the main statistical features of the return series across a wide range of assets. Hence, although it is by no means the optimal model for volatility forecasting in any given market, it does serve as a natural benchmark for the forecast performance of standard volatility models.

For the purpose of this research, the simple GARCH (1, 1) model will be adopted.

The literature on the day-of-the-week effect on stock market volatility has indicated the presence of the effect on different stock markets. However, little is known about the effect on the returns volatility of the South African stock market.

The evolution, disappearance and weakening of the effect because of improved market efficiency and maturity remains open. This aspect will be tested for the South African stock market.

# CHAPTER THREE: RESEARCH METHODOLOGY

# Chapter Three: Research Methodology

## 3.1. Introduction

This chapter describes the methodology adopted in gathering and analysing the data that enabled and provided answers to the objectives of the study and tested the hypothesis. The chapter is subdivided into sections that describe the research methodology and design, population and sample, research instruments, data-collection procedure, analysis and interpretation, and validity and reliability checks.

## 3.2. Research Methodology

The quantitative approach using a statistical analysis method was followed in conducting the research and in analysing the data.

## 3.3. Research Design

This research adopted mathematical modelling using the Ordinary Least Square methodology (OLS) and simple generalised autoregressive conditional heteroskedasticity (GARCH) model to test the presence of the day-of-the-week effect. The OLS took into consideration the lagged values of the returns variables, as well as allowing the variance of the error to be time dependent. The GARCH model developed by Bollerslev (1986) as an extension of Engle's (1982) autoregressive conditional heteroskedasticity (ARCH) model was used. This was based on the findings (Gregoriou, 2009) that the GARCH model is the most appropriate for forecasting stock market returns, is the workhorse of financial applications, and can describe the volatility dynamics of stock returns on most developed and emerging markets and most indices of equity returns.

The returns variance and volatility were determined from the log return of daily stock closing price.

## 3.4. Population and Sample

### *3.4.1. Population*

The population for the research is three indices of the JSE based on their full market capitalisations. The three indices are the JSE Top 40, the JSE Mid Cap and the JSE Small Cap indices. The compositions of these three indices are described in the fourth paragraph of this page and are a good representation of all companies listed on the JSE.

For all JSE-listed companies, each company is included in at least one of the JSE Headline indices. The eligible companies are ranked by full market capitalisation (before free float weightings are applied).

The top 99% of all companies are included in the JSE All Share index, with the remaining 1% forming the JSE Fledgling index.

The JSE All Share index is further divided into the JSE Top 40 index containing the 40highest-ranking companies, the JSE Mid Cap index containing the 60highest-ranking companies outside of the JSE Top 40 (i.e. companies ranked 41 to 100) and the JSE Small Cap index containing the remaining companies.

For a security to move into the JSE Top 40 index category, it must have risen to 35th position or above when the eligible securities are ranked by full market capitalisation. A security is removed from the JSE Top 40 index if it falls to 46th or below when the eligible securities are ranked by full market capitalisation.

A security is included in the JSE Mid Cap index if it has risen to 85$^{th}$ or above when the eligible securities are ranked by full market capitalisation. A security is removed from the JSE Mid Cap index if it falls to 116$^{th}$ or below when the eligible securities are ranked by full market capitalisation.

### 3.4.2. Sample and Sampling Method

The sample data consists of daily stock price data for each of the three JSE indices – i.e. JSE Top 40, JSE Mid Cap and JSE Small Cap indices– as representative of all companies listed on the JSE rather than studying individual companies or sectors.

The majority of studies on anomalies have focused on the investigation of the day-of-the-week effects on entire stock market indices. This study takes a microscopic view by grouping firms in their sizes defined by market-capitalisation indices that are likely to give a more accurate picture of anomalies.

The use of indices obviates the bias that could emanate from investors' tendencies to buy stocks from a certain sector on particular days and sell them on particular days. An example of such bias is the seasonal effects in the prices of commodities such as base metals, which determine the earnings of companies comprising basic materials whereby investors in the basic material sector seem to buy stocks on a Monday, resulting in higher returns on a Monday, and sell on a Friday resulting in lower returns on a Friday (Mbululu & Chipeta, 2012)

The data covering the daily stock prices from January 1996 to December 2010 will be analysed. This will involve analysing a total of 3915 daily data observations for the JSE Top 40, and 3716 observations for the JSE Mid Cap and the JSE Small Cap indices. The available data for the JSE Mid Cap and the JSE Small Cap starts from 15 March 1996.

## 3.5. The Research Instrument

This research adopted mathematical modelling using Ordinary Least Square methodology (OLS) and a simple generalised autoregressive conditional heteroskedasticity (GARCH) model developed by Bollerslev (1986) as an extension of Engle's (1982) autoregressive conditional heteroskedasticity (ARCH) model.

The returns variance was determined from log return of daily stock closing price.

## 3.6. Procedure for Data Collection

Stock prices for the period under study were obtained from the Johannesburg Stock Exchange (JSE). The stock price was downloaded through the World Equity Network (WEN) professional technical analysis system provided by PSG Online (Pty) Ltd, to which the researcher is a subscriber.

## 3.7. Data Analysis and Interpretation

Preliminary data analysis was conducted to assess the data in terms of normality, skewness, and kurtosis.

The study used log returns data to analyse the day-of-the-week effect on returns volatility on the stock market. The OLS and a simple GARCH model were used to estimate the returns volatility on the stock market.

The returns volatility model parameters were estimated using the maximum likelihood estimation approach.

## 3.7. Validity and Reliability

For research findings to be valid, the researcher must aim at reducing measurement error (Hair et al., 2010). In assessing the degree of measurement error present in any measure, validity and reliability characteristics become very important.

“Validity” refers to the extent to which a measure or set of measures correctly represents the concept of study, the degree to which it is free from any systematic or nonrandom error (Hair et al., 2010). The validity of an instrument determines the accuracy and credibility of the study. “Reliability”, on the other hand, refers to the consistency with which a measuring instrument yields certain results when the entity being measured has not changed (Hair et al., 2010).

In order to ensure that internal validity and reliability are achieved, appropriate statistical tools were used. Where major limitations exist and are encountered in data processing and analysis, they are disclosed in Section 1.7.

### *3.7.1. External validity*

For a conclusion drawn from research to be applicable beyond the research situation, the same study must be replicable in a different context and yield the same results (Hair et al., 2010). To ensure that the results drawn from this research are applicable to the South African stock market, the three indices selected are meant to represent companies listed on the JSE.

### *3.7.2. Reliability*

The fact that the stock price and all the data was collected and downloaded from the JSE database can serve as assurance of the reliability of the data gathered.

# CHAPTER FOUR:
# PRELIMINARY DATA ANALYSIS AND CHARACTERISATION

# Chapter Four: Preliminary Data Analysis and Characterisation

## 4.1 Introduction

This chapter characterises the JSE Top 40, the Mid Cap and the Small Cap indices returns data. The distribution nature of the returns data in terms of the mean returns, skewness and kurtosis for each day of the week for each of the three indices are examined. Also examined in this chapter are the probability plots of the returns data as compared to a normally distributed data probability plot. The chapter concludes by summarising the characteristics of the JSE three indices as observed form the preliminary analysis.

## 4.2 Analysis and Data Characterisation

The preliminary data analysis for the JSE Top 40, the JSE Mid Cap and the JSE Small Cap returns was conducted to determine the characteristics of the data and to establish whether the indices' returns behave in the same manner as other stock markets' returns. Table 1, Table 2 and Table 3 summarise the descriptive statistics of the JSE Top 40, the JSE Mid Cap and the JSE Small Cap returns respectively for each day of the week. The first column shows the day of the week, the second column reports the number of observations for each day of the week, the third column provides mean returns, the fourth column provides the standard deviation, and the fifth and sixth columns represent the skewness and kurtosis respectively.

From Table 1, Table 2 and Table 3, it can be observed that for the JSE Top 40, the JSE Mid Cap and the JSE Small Cap, the mean returns are positive for the duration under study, withtheexception of Friday for the JSE Top 40 where the daily mean return is negative. The mean returns range from -0.00002 to 0.00048 for the JSE Top 40, 0.00017 to 0.00030 for the JSE Mid Cap and 0.00011 to 0.00028 for the JSE Small Cap. The JSE Top 40 mean returns show a wider range among the days of the week compared to the JSE Mid Cap and the JSE Small Cap. The order of mean returns from the day with the highest to the lowest mean returns is Monday, Thursday, Wednesday, Tuesday and Friday for the JSE

Top 40; Thursday, Wednesday, Monday, Friday and Tuesday for the JSE Mid Cap; and Thursday, Friday, Wednesday, Tuesday and Monday for the JSE Small Cap.

The standard deviations for the JSE Top 40 range from 0.0059 to 0.0064, from 0.0038 to 0.0042 for the JSE Mid Cap, and those of the JSE Small Cap range from 0.0029 to 0.0035.

It was observed that for the JSE Top 40 the day with the highest mean returns was accompanied by the highest standard deviation while the day with the lowest mean returns also had thelowest standard deviation. For the JSE Mid Cap, although the day with thelowest mean returns also had the lowest standard deviation, the day with the highest mean returns was not accompanied by the highest standard deviation. The highest standard deviation went along with the day of the median returns. The observations for the JSE Small Cap are such that the day with the lowest mean returns had the highest standard deviation. The general trend does not indicate a consistent pattern with regard to the days with the highest/lowest mean returns having the highest/lowest standard deviations.

**Table 1: JSE Top 40 descriptive statistic summary**

| | **N** | **Mean** | **STD Dev.** | **Skewness** | **Kurtosis** |
|---|---|---|---|---|---|
| Monday | 783 | 0.00048 | 0.0064 | -0.807 | 5.869 |
| Tuesday | 783 | 0.00008 | 0.0063 | -1.128 | 13.847 |
| Wednesday | 783 | 0.00010 | 0.0063 | 0.093 | 4.324 |
| Thursday | 783 | 0.00024 | 0.0062 | -0.221 | 2.813 |
| Friday | 783 | -0.00002 | 0.0059 | 0.101 | 4.124 |

**Table 2: JSE Mid Cap descriptive statistic summary**

| | N | Mean | STD Dev. | Skewness | Kurtosis |
|---|---|---|---|---|---|
| Monday | 722 | 0.00022 | 0.0042 | -1.38 | 6.98 |
| Tuesday | 753 | 0.00017 | 0.0038 | -2.12 | 20.31 |
| Wednesday | 750 | 0.00025* | 0.0040 | -0.58 | 7.01 |
| Thursday | 750 | 0.00030 | 0.0039 | -1.18 | 11.14 |
| Friday | 737 | 0.00020 | 0.0038 | -0.95 | 7.39 |

**Table 3: JSE Small Cap descriptive statistic summary**

| | N | Mean | STD Dev. | Skewness | Kurtosis |
|---|---|---|---|---|---|
| Monday | 722 | 0.00011 | 0.0035 | -1.64 | 9.18 |
| Tuesday | 753 | 0.00012 | 0.0031 | -2.55 | 24.84 |
| Wednesday | 750 | 0.00023* | 0.0031 | -1.60 | 13.92 |
| Thursday | 750 | 0.00028 | 0.0032 | -3.00 | 29.59 |
| Friday | 737 | 0.00026* | 0.0029 | -1.79 | 13.31 |

** Statistically significant at 10% level*

***Statistically significant at 5% level*

**** Statistically significant at 1% level*

The results in Table 1, Table 2 and Table 3 indicate that for all weekdays for the three indices, except Wednesday and Friday for the JSE Top 40, the returns are negatively skewed, implying that the returns have left longer tails with returns concentrated on the right of the mean returns. The Wednesday and Friday returns for the JSE Top 40 are positively skewed and have right longer tails with returns concentrated to the left. Applied to investment returns (Mbululu & Chipeta, 2012), negative skewness implies frequent small gains and a few extreme losses. Positive skewness implies frequent small losses and a few extreme gains. A normal distribution has a skewness value of zero.

Table 1, Table 2 and Table 3 show that the returns of all three JSE indices exhibit a high level of kurtosis, indicating that these distributions have more peaked-ness and have fatter tails than normal distributions. With theexception of Thursday for the JSE Top 40, the kurtosis values obtained are higher than the kurtosis critical value of 3. The peaked-ness and fatter tails (based on kurtosis values) are higher for small firms and decrease with increasing size of the firm. The preliminary analysis shows that the JSE Top 40, the JSE Mid Cap and the JSE Small Cap daily returns are non-normally distributed around their mean returns and that they are leptokurtic and skewed.

Another test conducted for thenormality assumption for the JSE Top 40, the JSE Mid Cap and the JSE Small Cap returns was normal probability plots, which compare thecumulative distribution of the values of theactual returns data with the cumulative distribution of a normal distribution.

The normal probability plots are useful for assessing whether a given dataset follows a normal distribution. If the data set follows a normal distribution, the data points of the normal probability plots would fall along a straight line through the mean returns. The normal distribution forms a straight line when the values of the returns data are plotted alongside the normal distribution. Major deviations from this ideal picture reflect departures from normality. Stragglers at either end of the normal probability plot indicate outliers; curvature at both ends of the plot indicates long or short distributional tails; convex or concave curvature indicates a lack of symmetry; and gaps or plateaux or segmentation in the normal probability plot may require a closer examination of the data or model.

The normal probability plots were generated for each of the indices for all weekdays as well as for each day of the week (appendices A, B and C). Figure 2, Figure 3 and Figure 4 show the normal probability plots of returns for the JSE Top 40, the JSE Mid Cap and the JSE Small Cap respectively for all the days of the week for the duration under study. The day-of-the-week normal probability plots of returns for the JSE Top 40, the JSE Mid Cap and the JSE Small Cap are shown in the appendices in Figure A1-5, Figure B1-5 and Figure C1-5 respectively for Monday, Tuesday, Wednesday, Thursday and Friday.

Again, from Figure 2, Figure 3 and Figure 4, it can be observed that the JSE Top 40, the JSE Mid Cap and the JSE Small Cap data have curvatures at both ends of the plot, indicating long tails and non-symmetry.

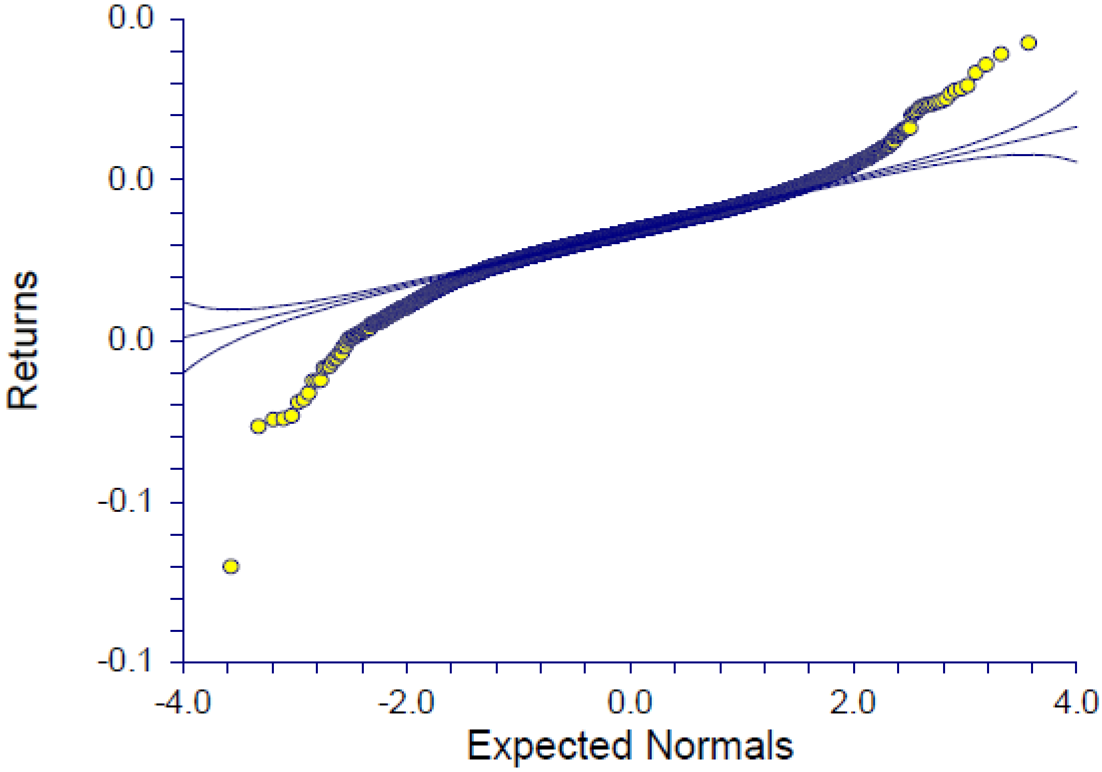


***Figure 2: Normal probability plots of returns (JSE Top 40)***

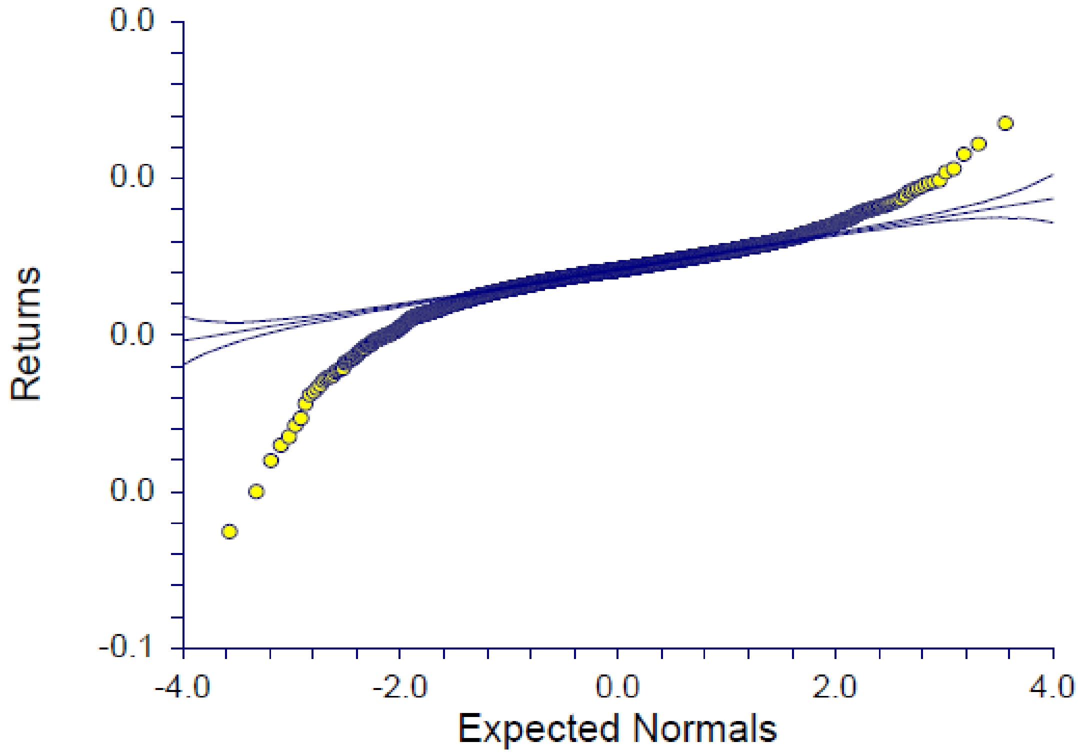


*Figure 3: Normal probability plots of returns (JSE Mid Cap)*

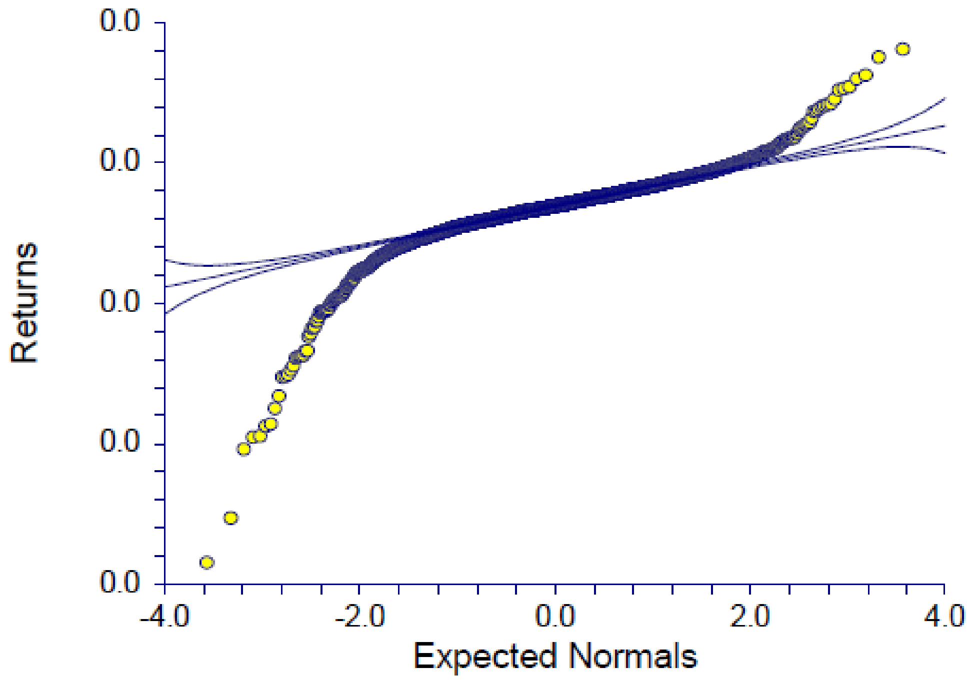


*Figure 4: Normal probability plots of returns (JSE Small Cap)*

## 4.3 Conclusion

Preliminary data characterisation conducted by means of an analysis of the descriptive statistics generated for each of the JSE Top 40, the JSE Mid Cap and the JSE Small Cap returns indicated that, with theexception of Friday for the JSE Top 40 where the mean return is negative, for all other weekdays the JSE Top 40, the JSE Mid Cap and the JSE Small Cap mean returns are positive for the period under study. The JSE Top 40 mean returns show a wider range among the days of the week compared to the JSE Mid Cap and the JSE Small Cap.

The mean returns versus thestandard deviation analysis did not show a consistent pattern with regard to the days with the highest/lowest mean returns having the associated highest/lowest standard deviations.

The skewness results indicated that for all weekdays for the three indices, except Wednesday and Friday for the JSE Top 40, the returns are negatively skewed, implying that the returns have left longer tails with returns concentrated on the right of the mean returns. The Wednesday and Friday returns for the JSE Top 40 are positively skewed and have right longer tails with returns concentrated to the left.

The descriptive statistics show that the returns of the three JSE indices exhibit high levels of kurtosis, meaning that these distributions have more peaked-ness and have fatter tails than normal distributions. Apart from Thursday for the JSE Top 40, the kurtosis values obtained are higher than the kurtosis critical value of 3. The peaked-ness and fatter tails (based on kurtosis values) are higher for small firms and decrease with increasing size of the firm.

The normal probability plots indicated that the data for the JSE Top 40, the JSE Mid Cap and the JSE Small Cap daily returns have curvatures at both ends of the plot, indicating long tails and non-symmetry. The plots show that the indices are non-normally distributed around their mean and that they are leptokurtic and skewed.

# CHAPTER FIVE: MODELLING THE DAY-OF-THE-WEEK EFFECT ON STOCK MARKET RETURNS VOLATILITY

# Chapter Five: Modelling the Day-of-the-Week Effect on Stock Market Returns Volatility

## 5.1 Introduction

In this chapter, theday-of-the-week effect on returns and returns volatility is modelled for each of the JSE Top 40, the JSE Mid Cap and the JSE Small Cap for the 1996- to 2010 period is described.

The chapter has been grouped into four sections. The first section of the chapter presents the day-of-the-week effect on returns equation analysis; and the second section presents the day-of-the-week effect on returns volatility equation analysis. In the third section of the chapter, the first hypothesis postulated in Section (2.5.1) is tested whilst the fourth section summarises the findings of the chapter.

## 5.2 Effect on returns equation

The investigation and analysis of the day-of-the-week effect on returns employed the OLS methodology by regressing return on the five daily dummy variables.

In order to address the drawbacks of autocorrelation, the lagged values of the return variable were included in the OLS equation (Equation 4). To address the second drawback of non-constant variance, the variances of the error were allowed to be time dependent to include a conditional heteroskedasticity that captures the variation of variance in stock returns.

The estimates of the day-of-the-week returns variables coefficients obtained using Equation 4 are reported in Table 4, Table 5 and Table 6 for the JSE Top 40, the JSE Mid Cap and the JSE Small Caps respectively.

From Table 4, Table 5 and Table 6 it can be observed that the highest/lowest returns coefficients among the three indices do not occur on the same days of the week.

The results of the estimates indicated that for the JSE Top 40 index Monday has the highest returns coefficient, implying that it has the highest mean returns of all the weekdays. The second weekday with a higher returns equation coefficient is Thursday. Tuesday was observed to have the lowest returns equation coefficient, implyingthelowest mean returns.

With the JSE Mid Cap and the JSE Small Cap, Friday was observed to have thehighest returns equation coefficient (thus higher mean returns) followed by Thursday. As with the JSE Top 40, Tuesday was observed to have the lowest returns equation coefficient for the JSE Mid Cap while Monday and Tuesday were observed to have similar and thelowest returns equation coefficients for the JSE Small Cap.

The significance of the returns equation coefficients was tested at the 10%, 5% and 1% confidence levels. The results indicated that for the JSE Top 40, Monday and Thursday returns equation coefficients were statistically significant at all three levels. The Tuesday, Wednesday and Friday returns equation coefficients were observed to be insignificant at any of the three confidence levels.

For the JSE Mid Cap, the returns equation coefficients for Thursday and Friday were observed to be statistically significant at the 1%, while they were found to be statistically significant at the 5% for Monday and Wednesday. The Tuesday returns equation coefficient was observed to be insignificant at any of the 10%, 5% and 1% confidence levels.

The returns equation coefficients for the JSE Small Cap were observed to be statistically significant at the 1% for Thursday and Friday, at the 5% for Wednesday, Thursday and Friday, while the returns equation coefficients for Monday and Tuesday were only statistically significant at 10%.

Compared to other stock markets observed by Kiymaz and Berument (2003), the lowest returns coefficient of Tuesday for the JSE Top 40, the JSE Mid Cap and the JSE Small Cap (the returns equation coefficients for Monday and Tuesday were similar for the JSE Small Cap) corresponded to the same lowest returns day for Japan. The highest returns for the JSE Top 40, the JSE Mid Cap and the JSE Small cap did not occur on the same day. While the JSE Top 40 index's highest returns occurred on Monday, none of the other countries' stock markets had the highest returns on Monday. The highest returns day of Friday for the JSE Mid Cap and the JSE Small Cap corresponded to the highest day of the week for Canada's stock market.

**Table 4: Weekday coefficients in returns equation (JSE Top 40)**

| Day of the Week | Coefficient | STD | 90% Confidence Interval | | 95% Confidence Interval | | 99% Confidence Interval | |
|---|---|---|---|---|---|---|---|---|
| | | | Lower Limit | Higher Limit | Lower Limit | Higher Limit | Lower Limit | Higher Limit |
| Monday | 0.00065 | 0.00017 | 0.00037 | 0.00094 | 0.00031 | 0.00099 | 0.00020 | 0.00110 |
| Tuesday | 0.00009 | 0.00016 | -0.00017 | 0.00035 | -0.00022 | 0.00040 | -0.00031 | 0.00050 |
| Wednesday | 0.00020 | 0.00017 | -0.00008 | 0.00048 | -0.00013 | 0.00054 | -0.00024 | 0.00064 |
| Thursday | 0.00047 | 0.00016 | 0.00021 | 0.00073 | 0.00016 | 0.00078 | 0.00006 | 0.00088 |
| Friday | 0.00023 | 0.00018 | -0.00006 | 0.00053 | -0.00012 | 0.00058 | -0.00023 | 0.00069 |

**Table 5: Weekdays coefficients in returns equation (JSE Mid Cap)**

| Day of the Week | Coefficient | STD | 90% Confidence Interval | | 95% Confidence Interval | | 99% Confidence Interval | |
|---|---|---|---|---|---|---|---|---|
| | | | Lower Limit | Higher Limit | Lower Limit | Higher Limit | Lower Limit | Higher Limit |
| Monday | 0.00027 | 0.00011 | 0.00008 | 0.00045 | 0.00005 | 0.00048 | -0.00002 | 0.00055 |
| Tuesday | 0.00015 | 0.00010 | -0.00001 | 0.00032 | -0.00004 | 0.00035 | -0.00011 | 0.00041 |
| Wednesday | 0.00029 | 0.00011 | 0.00010 | 0.00048 | 0.00007 | 0.00052 | -0.00000 | 0.00059 |
| Thursday | 0.00034 | 0.00011 | 0.00016 | 0.00052 | 0.00013 | 0.00055 | 0.00006 | 0.00062 |
| Friday | 0.00041 | 0.00010 | 0.00025 | 0.00057 | 0.00022 | 0.00060 | 0.00016 | 0.00066 |

**Table 6: Weekday coefficients in returns equation (JSE Small Cap)**

| Day of the Week | Coefficient | STD | 90% Confidence Interval | | 95% Confidence Interval | | 99% Confidence Interval | |
|---|---|---|---|---|---|---|---|---|
| | | | Lower Limit | Higher Limit | Lower Limit | Higher Limit | Lower Limit | Higher Limit |
| Monday | 0.00015 | 0.00009 | 0.00000 | 0.00029 | -0.00002 | 0.00032 | -0.00008 | 0.00038 |
| Tuesday | 0.00015 | 0.00008 | 0.00002 | 0.00028 | -0.00000 | 0.00030 | -0.00005 | 0.00035 |
| Wednesday | 0.00019 | 0.00008 | 0.00005 | 0.00032 | 0.00003 | 0.00035 | -0.00002 | 0.00040 |
| Thursday | 0.00034 | 0.00008 | 0.00021 | 0.00047 | 0.00018 | 0.00050 | 0.00013 | 0.00055 |
| Friday | 0.00045 | 0.00007 | 0.00033 | 0.00056 | 0.00031 | 0.00059 | 0.00026 | 0.00063 |

## 5.3 Effect on returns volatility equation

The change in the conditional variance of returns among the days of the week was modelled using the simple GARCH equation for conditional variance of returns. This enabled the detection of the existence of the day-of-the-week effect on volatility. The dummy variable for Monday was excluded in returns volatility coefficient determination. Only four days (Tuesday, Wednesday, Thursday and Friday) of the week's dummy variables were included. The results from the conditional variance (GARCH) equation are presented in Table 7, Table 8 and Table 9 for the JSE Top 40, the JSE Mid Cap and the JSE Small Cap respectively.

The conditional variance equation coefficients indicated that for the JSE Top 40 index Thursday has the highest returns volatility. The results indicate that Friday has the lowest volatility compared to the other days of the week. The test for conditional variance coefficient significance at the 1% significance level indicated that Monday's volatility was only significant at 10%. Friday's volatility was observed to be significant at the 1% confidence level. Tuesday, Wednesday and Thursday were insignificant at any of the three confidence levels tested. However, given that there is no statistical significance at the 10%, 5% and 1% levels for the other days of the week, the results suggest the non-existence of the day-of-the-week effect in returns volatility for the JSE Top 40 index at the three confidence levels for Tuesday, Wednesday and Thursday.

The JSE Mid Cap conditional variance equation coefficient indicated that Wednesday has the highest returns volatility while Friday has the lowest returns volatility.

The conditional variance equation coefficients for the JSE Mid Cap for Monday, Tuesday, Wednesday Thursday and Friday were found to be statistically insignificant at the 10% level, implying the non-existence of the effect of day of the week on volatility for the JSE Mid Cap.

The Monday conditional variance equation coefficient for the JSE Small Cap was found to be the highest, implying the highest volatility. Friday's was the lowest. The coefficients for Monday, Tuesday, Thursday and Friday were found to be statistically significant at the 10% confidence level. Wednesday's coefficient was found to be significant at the 10% and 5% confidence levels only.Indeed, the day-of-the-week effects on the JSE Small Cap returns volatility equation was detected for Monday, Tuesday, Thursday and Friday at the 1% confidence level, and on Wednesday at the 5% confidence level.

The results indicated that the JSE Top 40 index's highest volatility of returns, which occurred on Thursdays, was on the same day as that for the UK, as was observed by Kiymaz and Berument (2003). In contrast, the day of the week with the highest volatility of returns (Wednesday) for the JSE Mid Cap did not correspond to any of the developed stock markets studied by Kiymaza and Berument (2003), while the highest volatility of returns day (Monday) for the JSE Small Cap corresponded to Germany's and Japan's.

The results indicated that the three JSE indices studied (i.e. the JSE Top 40, the JSE Mid Cap and the JSE Small Cap) had their lowest returns volatility on Fridays. The lowest returns volatility day of a Friday did not correspond to any lowest volatility of returns day for any of the developed stock markets studied by Kiymaz and Berument (2003).

**Table 7: Weekday coefficients of conditional variances in GARCH returns volatility equation (JSE Top 40)**

| Day of the Week | Coefficient | STD | 90% Confidence Interval | | 95% Confidence Interval | | 99% Confidence Interval | |
|---|---|---|---|---|---|---|---|---|
| | | | Lower Limit | Higher Limit | Lower Limit | Higher Limit | Lower Limit | Higher Limit |
| Constant | 1.84E-06 | 9.45E-07 | 2.83E-07 | 3.39E-06 | -1.46E-08 | 3.69E-06 | -5.97E-07 | 4.27E-06 |
| Tuesday | -1.25E-06 | 1.56E-06 | -3.81E-06 | 1.31E-06 | -4.31E-06 | 1.80E-06 | -5.27E-06 | 2.76E-06 |
| Wednesday | -5.61E-08 | 1.52E-06 | -2.56E-06 | 2.44E-06 | -3.03E-06 | 2.92E-06 | -3.97E-06 | 3.86E-06 |
| Thursday | 6.72E-07 | 1.33E-06 | -1.51E-06 | 2.85E-06 | -1.93E-06 | 3.27E-06 | -2.74E-06 | 4.09E-06 |
| Friday | -5.18E-06 | 1.55E-06 | -7.73E-06 | -2.62E-06 | -8.22E-06 | -2.13E-06 | -9.18E-06 | -1.17E-06 |

**Table 8: Weekday coefficients of conditional variances in GARCH returns volatility equation (JSE Mid Cap)**

| Day of the Week | Coefficient | STD | 90% Confidence Interval | | 95% Confidence Interval | | 99% Confidence Interval | |
|---|---|---|---|---|---|---|---|---|
| | | | Lower | Higher Limit | Lower | Higher Limit | Lower Limit | Higher Limit |
| Constant | 3.76E-07 | 3.92E-07 | -2.69E-07 | 1.02E-06 | -3.92E-07 | 1.14E-06 | -6.34E-07 | 1.39E-06 |
| Tuesday | 1.49E-07 | 6.53E-07 | -9.26E-07 | 1.22E-06 | -1.13E-06 | 1.43E-06 | -1.53E-06 | 1.83E-06 |
| Wednesday | 7.14E-07 | 5.55E-07 | -1.99E-07 | 1.63E-06 | -3.74E-07 | 1.80E-06 | -7.16E-07 | 2.14E-06 |
| Thursday | 1.39E-07 | 5.17E-07 | -7.12E-07 | 9.90E-07 | -8.75E-07 | 1.15E-06 | -1.19E-06 | 1.47E-06 |
| Friday | -3.61E-07 | 6.50E-07 | -1.43E-06 | 7.09E-07 | -1.64E-06 | 9.14E-07 | -2.04E-06 | 1.31E-06 |

**Table 9: Weekday coefficients of conditional variances in GARCH returns volatility equation (JSE Small Cap)**

| Day of the Week | Coefficient | STD | 90% Confidence Interval | | 95% Confidence Interval | | 99% Confidence Interval | |
|---|---|---|---|---|---|---|---|---|
| | | | Lower Limit | Higher Limit | Lower Limit | Higher Limit | Lower Limit | Higher Limit |
| Constant | 1.52E-06 | 2.01E-07 | 1.19E-06 | 1.85E-06 | 1.12E-06 | 1.91E-06 | 9.98E-07 | 2.03E-06 |
| Tuesday | -1.37E-06 | 3.16E-07 | -1.89E-06 | -8.51E-07 | -1.99E-06 | -7.51E-07 | -2.18E-06 | -5.56E-07 |
| Wednesday | -7.79E-07 | 3.04E-07 | -1.28E-06 | -2.79E-07 | -1.37E-06 | -1.83E-07 | -1.56E-06 | 4.04E-09 |
| Thursday | -9.14E-07 | 2.79E-07 | -1.37E-06 | -4.55E-07 | -1.46E-06 | -3.68E-07 | -1.63E-06 | -1.96E-07 |
| Friday | -1.57E-06 | 3.44E-07 | -2.13E-06 | -1.00E-06 | -2.24E-06 | -8.92E-07 | -2.45E-06 | -6.80E-07 |

## 5.4 Hypothesis testing

The first hypothesis was built from Section 2.3, where it was observed that in developed and emerging stock markets, the day of the week had been shown to have an effect on the stock market returns volatility. It was also learnt that the day-of-the-week effect was not constant (i.e. the trend in the effect was not the same) among the different stock markets).

The null hypothesis was postulated as ”there is no significant difference in stock market returns volatility among the days of the week in the South African stock market” whereas the alternative hypothesis was postulated as “there is significant difference in stock market volatility among the days of the week in the South African stock market”.

The test for significance at the 10%, 5% and 1% confidence levels indicated that only Friday’s conditional variance equation coefficient was significant at the three levels for the JSE Top 40. The Monday conditional variance equation coefficient was only significant at 10%. The other weekday coefficients were insignificant at all three levels. On the basis of these observations, the null hypothesis is accepted for Tuesday, Wednesday and Thursday for the JSE Top 40. The alternative hypothesis is rejected for these three days. However, the Friday effect at the 10%, 5% and 1% significance levels and theMonday effect at the 10%significance level was observed and therefore the null hypothesis for these conditions for Fridays and Mondays is rejected.

For the JSE Mid Cap, the conditional variance equation coefficients were insignificant at the three confidence levels for Monday, Tuesday, Wednesday, Thursday and Friday. On the basis of these findings, the null hypothesis is accepted for the JSE Mid Cap returns volatility. Conversely, the alternative hypothesis is rejected.

With the JSE Small Cap, the conditional variance equation coefficients for Monday, Tuesday, Thursday and Friday were found to be statistically significant at the 1% confidence level and that of Wednesday was significant at 5%. Indeed, the day-of-the-week effects on the JSE Small Cap returns volatility equation was detected for Monday, Tuesday, Thursday and Friday at the 1% confidence level and Wednesday at 5% confidence level. The null hypothesis is rejected for all the weekdays at the 10% confidence levels. At the1% confidence level, the null hypothesis is rejected for Monday, Tuesday, Thursday and Friday. The alternative hypothesis is accepted under the condition of null hypothesis rejection.

## 5.5 Conclusion

In analysing the day-of-the-week effect on the volatility JSE stock market returns, the OLS returns equation, taking into consideration the lagged values of the return variables and allowing the variance of the error to be time dependent, was used to model the returns and the simple GARCH model was used to model and determine the volatility of the returns.

The returns and conditional variance equations coefficients were estimated.

The returns equation coefficients indicated that for the JSE Top 40 Monday has the highest mean returns whilst Tuesday has the lowest mean returns. The highest mean returns day was in agreement with the observation made during thepreliminary analysis. However, the day with the lowest mean returns observed fromthemodelling differs from that observed during thepreliminary data analysis.

Friday’s mean returns were observed to be the highest for JSE Mid Cap and JSE Small Cap. Like the JSE Top 40, Tuesday was observed to have the lowest mean returns.

The day-of-the-week effect in returns was only detected for Monday and Thursday for the JSE Top 40 index.

For the JSE Mid Cap, the day-of-the-week effect in returns was found at 10% and 5% for Monday, Wednesday, Thursday and Friday and on Thursday and Friday at the 1% confidence level. The returns equation coefficients for the JSE Small Cap were observed to be statistically significant at 10%, 5% and 1% for Thursday and Friday, at 10% and 5% for Wednesday, while the returns equation coefficients for Monday and Tuesday were only statistically significant at 10%.

The conditional variance equation coefficients indicated that Thursday has the highest returns volatility for the JSE Top 40. The JSE Mid Cap and JSE Small Cap have their highest returns volatility on Wednesday and Monday respectively. For all the indices, Friday was observed to have the lowest returns volatility.

The analyses of the significance levels suggest that the day of the week has an effect on JSE stock market returns volatility for the JSE Small Cap index. The results do not show a strong presence of the day of the week in results for the JSE Top 40 while the day of the week has no significance for the JSE Mid Cap index.

# CHAPTER SIX: VARIATION OF THE DAY-OF-THE-WEEK EFFECT DURING SUB-PERIODS

# Chapter Six: Variation of the Day-of-the-Week Effect During Sub-Periods

## 6.1 Introduction

It has been argued (Kohers et al., 2004) that due to improvement in market efficiency over time or as a result of markets maturing, the day-of-the-week effect has disappeared, weakened and/or reversed.

Philpot and Peterson (2011) reported shift and reversal of the weekend effect for larger-firm securities observed by Pettengill (1989). When examining large-firm returns separately from those of small firms, (Pettengill, 1989) found that the weekend effect tends to reverse itself over sub-periods within longer sample periods, including the years 1963 to 1989. Specifically, for large firms the effect begins as a significant negative Monday effect, then becomes a non-significant negative effect, then eventually progresses on average to positive and significant.

The study to investigate the disappearance, weakening and/or reversal of the day-of-the-week effect on the JSE stock market was conducted using the JSE Top 40 index data.

The returns data from January 1996 to December 2010 for the index was split into three five-year sub-periods (i.e. January 1996 to December 2000, January 2001 to December 2005 and January 2006 to December 2010). The data was then modelled using the OLS (taking into consideration the lagged values of the return variables and allowing the variance of the error to be time dependent) and GARCH models to determine the day-of-the-week effect on returns and returns volatility equations respectively for each of the sub-periods. The effect of the day of the week on returns and returns volatility equations is discussed in sections 6.2 and 6.3 respectively.

Despite literature indicating various studies carried out to investigate the disappearance, weakening and/or reversal of the effect, most research studied the effect on returns. Not much information related to the disappearance, weakening and/or reversal of the effect on returns volatility.

## 6.2 Effect on returns equation during sub-Periods

In order to investigate the effect of the day of the week on returns equation during the three sub-periods, the same approach as used in Section 5.1 was adopted.

The day-of-the-week return equation coefficients were estimated using Equation 4 and the estimated coefficients are reported in Table 10, Table 11 and Table 12 for the JSE Top 40 index for January 1996 to December 2000, January 2001 to December 2005 and January 2006 to December 2010 respectively.

The returns equation coefficients for the five weekdays for the 1996 to 2000 sub-period are negative. Those for the 2001 to 2005 sub-period are negative, except for Tuesday, and those for the 2006 to 2010 sub-period, except for Monday, are also negative. This observation differs from that for the entire 1996 to 2010 period reported in Table 4. While the reason(s) that has (have) led to the returns equation coefficients for the sub-periods being mostly negative compared to the entire 1996 to 2010 period returns equation coefficients has not been established, further study could provide more insight as to what the reason could be.

The results for the returns equation coefficients indicated that the days with the highest returns were Thursday, Tuesday and Monday for the 1996 to 2000, 2001 to 2005 and 2006 to 2010 sub-periods respectively. The lowest returns days were observed to be Monday, Thursday and Friday for 1996 to 2000, 2001 to 2005 and 2006 to 2010 sub-periods respectively. What can be observed is that Monday shifted from being the lowest returns day for the 1996 to 2000 sub-period to the highest returns day for the 2006 to 2010 sub-period. Thursday shifted from being the highest returns day for the 1996 to 2000 sub-period to the lowest returns day from 2001 to 2005 before it changed place with Friday in 2006 to 2010.

Compared to the results from Table 4 where the returns equation coefficients are indicated for the entire 1996 to 2010 returns data, Monday was observed to be the highest returns day. This is the same as observed for the 2006 to 2010. However, none of the three sub-periods' lowest returns day corresponds to the lowest returns day for the entire 1996 to 2010 period.

The significance test at 10%, 5% and 1% indicated that for the 1996 to 2000 sub-period none of the five coefficients was significant at any level. In the case of the 2001 to 2005 sub-period, the returns equation coefficient for Wednesday was observed to be statistically significant at the three levels whilst for Friday; the returns equation coefficient was statistically significant at the 5% confidence level. Monday, Tuesday and Thursday's returns equation coefficients were statistically insignificant at any of the three confidence levels tested.

For the 2006 to 2010 sub-period, the returns equation coefficients for Monday and Thursday were insignificant at any of the three confidence levels while those for Tuesday, Wednesday and Friday were significant at the 5% confidence level.

Although the returns equation coefficients for Monday and Thursday for the entire duration analysis (Table 4) were found to be statistically significant to at least 10%, for the three sub-periods, the returns coefficients (Table 10, Table 11 and Table 12) for the two days were found to be statistically insignificant at all three levels.

The results paint a different picture from other previous studies into developed stock markets. Whilst Kohers et al., ( 2004) and Steely (2001) studies suggested disappearance of the effect in recent years due to long run improvement in market efficiency, the results of this study for the JSE Top 40 index indicated the effect on returns being insignificant during the 1996 to 2000, becoming significant for Wednesday during 2001 to 2005 sub-period and significant at 5% confidence level for Tuesday, Wednesday and Friday.

**Table 10: Weekday coefficients in returns equation (JSE Top 40: 1996-2000)**

| Day of the Week | Coefficient | STD | 90% Confidence Interval | | 95% Confidence Interval | | 99% Confidence Interval | |
|---|---|---|---|---|---|---|---|---|
| | | | Lower Limit | Higher Limit | Lower Limit | Higher Limit | Lower Limit | Higher Limit |
| Monday | -0.00079 | 0.00066 | -0.00188 | 0.00030 | -0.00209 | 0.00051 | -0.00250 | 0.00091 |
| Tuesday | -0.00073 | 0.00060 | -0.00171 | 0.00026 | -0.00190 | 0.00045 | -0.00227 | 0.00082 |
| Wednesday | -0.00047 | 0.00074 | -0.00168 | 0.00075 | -0.00191 | 0.00098 | -0.00237 | 0.00144 |
| Thursday | -0.00022 | 0.00069 | -0.00137 | 0.00092 | -0.00159 | 0.00114 | -0.00201 | 0.00157 |
| Friday | -0.00059 | 0.00059 | -0.00155 | 0.00038 | -0.00174 | 0.00056 | -0.00210 | 0.00092 |

**Table 11: Weekday coefficients in returns equation (JSE Top 40: 2001-2005)**

| Day of the Week | Coefficient | STD | 90% Confidence Interval | | 95% Confidence Interval | | 99% Confidence Interval | |
|---|---|---|---|---|---|---|---|---|
| | | | Lower Limit | Higher Limit | Lower | Higher Limit | Lower Limit | Higher Limit |
| Monday | -0.00028 | 0.00065 | -0.00135 | 0.00080 | -0.00156 | 0.00101 | -0.00196 | 0.00141 |
| Tuesday | 0.00096 | 0.00068 | -0.00016 | 0.00209 | -0.00038 | 0.00231 | -0.00080 | 0.00273 |
| Wednesday | -0.00228 | 0.00067 | -0.00339 | -0.00118 | -0.00360 | -0.00097 | -0.00402 | -0.00055 |
| Thursday | -0.00095 | 0.00067 | -0.00206 | 0.00015 | -0.00227 | 0.00037 | -0.00269 | 0.00078 |
| Friday | -0.00179 | 0.00070 | -0.00294 | -0.00065 | -0.00316 | -0.00043 | -0.00359 | 0.00000 |

**Table 12: Weekday coefficients in returns equation (JSE Top 40: 2006-2010)**

| Day of the Week | Coefficient | STD | 90% Confidence Interval | | 95% Confidence Interval | | 99% Confidence Interval | |
|---|---|---|---|---|---|---|---|---|
| | | | Lower Limit | Higher Limit | Lower | Higher Limit | Lower Limit | Higher Limit |
| Monday | 0.00061 | 0.00092 | -0.00090 | 0.00212 | -0.00119 | 0.00241 | -0.00175 | 0.00297 |
| Tuesday | -0.00161 | 0.00074 | -0.00282 | -0.00040 | -0.00305 | -0.00016 | -0.00351 | 0.00029 |
| Wednesday | -0.00177 | 0.00082 | -0.00312 | -0.00042 | -0.00338 | -0.00016 | -0.00389 | 0.00034 |
| Thursday | -0.00058 | 0.00078 | -0.00186 | 0.00070 | -0.00210 | 0.00094 | -0.00258 | 0.00142 |
| Friday | -0.00206 | 0.00090 | -0.00355 | -0.00057 | -0.00383 | -0.00029 | -0.00439 | 0.00027 |

## 6.3 Effect on volatility equation during sub-Periods

The study of the disappearance, weakening and/or reversal of the returns volatility for the three sub-periods (January 1996 to December 2000, January 2001 to December 2005 and January 2006 to December 2010) were conducted using the same approach described in Section 5.3.

The conditional variances of returns (returns volatility) were estimated using the simple GARCH model. The coefficients of the conditional variance of returns equation estimated are reported in Table 13, Table 14 and Table 15 alongside their respective standard deviations and confidence intervals for the 1996 to 2000, 2001 to 2005 and 2006 to 2010 sub-periods respectively. The dummy variable for Monday was excluded in the determination of the conditional variances of returns equation coefficients.

The conditional variance equation coefficients (Table 13, Table 14 and Table 15) indicated that Monday for the 1996 to 2000 and Friday for the 2001 to 2005 and 2006 to 2010 sub-periods have the highest returns volatility compared to the other weekdays for their respective sub-periods. Friday for 1996 to 2000 sub-period, Thursday for 2001 to 2005 sub-period and Monday for 2006 to 2010 sub-period have the lowest returns volatility.

The confidence interval analyses indicated that for the 1996 to 2000 sub-period, the conditional variance equation coefficients for Monday and Thursday were only significant at the 10% confidence level. The coefficient for Friday was significant at the 1% confidence level.

The conditional variance equation coefficients for the 2001 to 2005 and 2006 to 2010 sub-periods were all insignificant at the three confidence levels. Even Monday and Tuesday which were significant at 10% confidence level for 1996-2000 seize to be significant.

Comparing the conditional variance equation coefficient significance for the three sub-periods and those for the entire 1996 to 2010 for the JSE Top 40 index, one observes some similarities between those of the 1996 to 2000 sub-period and those of the 1996 to 2010 period. The 1996 to 2000 sub-period and the entire 1996 to 2010 period have the Monday coefficient significant at the 10% confidence level while the coefficients for Friday were significant at all three levels.

Given that the coefficients for the 2001 to 2005 and 2006 to 2010 sub-periods were insignificant at any of the three levels, one asks oneself whether the entire 1996 to 2010 period's Monday and Friday significances are not influenced by the 1996 to 2000 sub-period.

The results of the Day-of-the-week-effect on returns volatility during the three sub-periods paint a picture similar to the observations made by Kohers et al. ( 2004) and Steely (2001) whereby they observed the disappearance of the effect with years as the market efficiency improves over the long run.

**Table 13: Weekday coefficients of conditional variances in GARCH returns volatility equation (JSE Top 40: 1996-2000)**

| Day of the Week | Coefficient | STD | 90% Confidence Interval | | 95% Confidence Interval | | 99% Confidence Interval | |
|---|---|---|---|---|---|---|---|---|
| | | | Lower Limit | Higher Limit | Lower | Higher Limit | Lower Limit | Higher Limit |
| Constant | 1.65E-05 | 8.58E-06 | 2.38E-06 | 3.06E-05 | -3.33E-07 | 3.33E-05 | -5.63E-06 | 3.86E-05 |
| Tuesday | -2.51E-05 | 1.58E-05 | -5.12E-05 | 9.39E-07 | -5.62E-05 | 5.94E-06 | -6.59E-05 | 1.57E-05 |
| Wednesday | 6.64E-06 | 1.15E-05 | -1.22E-05 | 2.55E-05 | -1.58E-05 | 2.91E-05 | -2.29E-05 | 3.62E-05 |
| Thursday | -2.07E-05 | 1.20E-05 | -4.04E-05 | -1.02E-06 | -4.42E-05 | 2.76E-06 | -5.16E-05 | 1.02E-05 |
| Friday | -3.02E-05 | 1.13E-05 | -4.88E-05 | -1.16E-05 | -5.23E-05 | -8.03E-06 | -5.93E-05 | -1.05E-06 |

**Table 14: Weekday coefficients of conditional variances in GARCH returns volatility equation (JSE Top 40: 2001-2005)**

| Day of the Week | Coefficient | STD | 90% Confidence Interval | | 95% Confidence Interval | | 99% Confidence Interval | |
|---|---|---|---|---|---|---|---|---|
| | | | Lower Limit | Higher Limit | Lower Limit | Higher Limit | Lower Limit | Higher Limit |
| Constant | -3.90E-06 | 1.01E-05 | -2.06E-05 | 1.28E-05 | -2.38E-05 | 1.60E-05 | -3.00E-05 | 2.22E-05 |
| Tuesday | 8.57E-06 | 1.67E-05 | -1.89E-05 | 3.61E-05 | -2.42E-05 | 4.14E-05 | -3.46E-05 | 5.17E-05 |
| Wednesday | 1.31E-05 | 1.51E-05 | -1.17E-05 | 3.79E-05 | -1.64E-05 | 4.27E-05 | -2.58E-05 | 5.20E-05 |
| Thursday | -9.67E-06 | 1.65E-05 | -3.69E-05 | 1.76E-05 | -4.21E-05 | 2.28E-05 | -5.24E-05 | 3.30E-05 |
| Friday | 2.12E-05 | 1.88E-05 | -9.80E-06 | 5.21E-05 | -1.57E-05 | 5.81E-05 | -2.74E-05 | 6.97E-05 |

**Table 15: Weekday coefficients of conditional variances in GARCH returns volatility equation (JSE Top 40: 2006-2010)**

| Day of the Week | Coefficient | STD | 90% Confidence Interval | | 95% Confidence Interval | | 99% Confidence Interval | |
|---|---|---|---|---|---|---|---|---|
| | | | Lower | Higher Limit | Lower Limit | Higher Limit | Lower Limit | Higher Limit |
| Constant | -7.86E-06 | 1.26E-05 | -2.87E-05 | 1.30E-05 | -3.27E-05 | 1.70E-05 | -4.05E-05 | 2.48E-05 |
| Tuesday | 1.28E-06 | 2.10E-05 | -3.33E-05 | 3.59E-05 | -4.00E-05 | 4.25E-05 | -5.29E-05 | 5.55E-05 |
| Wednesday | 2.99E-05 | 1.94E-05 | -2.13E-06 | 6.18E-05 | -8.26E-06 | 6.80E-05 | -2.03E-05 | 8.00E-05 |
| Thursday | -1.41E-07 | 2.20E-05 | -3.63E-05 | 3.60E-05 | -4.32E-05 | 4.30E-05 | -5.68E-05 | 5.65E-05 |
| Friday | 3.13E-05 | 2.24E-05 | -5.61E-06 | 6.82E-05 | -1.27E-05 | 7.53E-05 | -2.66E-05 | 8.92E-05 |

## 6.4 Hypothesis testing

The second hypothesis was built on the basis of observations made in Section 2.4, where it was claimed that the effect of the day of the week on stock market returns volatility has disappeared and/or is weakening and/or reversing as a result of improvement in market efficiency and maturity. However, there is evidence that the effect still exists and has not been shown to disappear or weaken, as claimed by a few authors.

The null hypothesis was postulated as “the day-of-the-week effect on returns volatility has disappeared in the South African stock market” whereas the alternative hypothesis was postulated as “the day-of-the-week effect on returns volatility has not disappeared in the South African stock market”.

The test for significance at the 10%, 5% and 1% confidence levels indicated that Monday and Thursday’s conditional variance equation coefficients were only significant at the 10% confidence level for the 1996 to 2000 sub-period. For the same sub-period, Friday’s conditional variance equation coefficient was significant at the 1% confidence level.

The conditional variance equation coefficients for the 2001 to 2005 and 2006 to 2010 sub-periods were all insignificant at the three confidence levels.

On this basis, where it is observed that none of the coefficients for 2001 to 2005 and 2006 to 2010 were significant at any confidence level and that for Monday and Friday the conditional variance equation coefficients were significant for at least the 10% confidence levels, the null hypothesis for Monday and Friday is accepted for the JSE Top 40 index for the sub-periods studied. Conversely, the alternative hypothesis is rejected.

## 6.5 Conclusion

The analysis of the returns equation coefficients indicated that for the 1996 to 200 sub-period, Thursday had the highest returns whilst Monday had the lowest; for the 2001 to 2005 sub-period, Tuesday's returns were the highest while Thursday's were lowest; and for 2006 to 2010 sub-period, Monday had highest returns and Friday the lowest.

The day-of-the-week effect in returns equation was detected for Wednesday and Friday at 10%, 5% and 1% for the 2001 to 2005 sub-period and on Tuesday, Wednesday and Friday at 10% and 5% for the 2006 to 2010 sub-periods. The results show the appearance of the day-of-the-week effect in returns equation in the 2001 to 2005 and 2006 to 2010 sub-periods, which was not observed in the 1996 to 2000 sub-period.

The conditional variance equation coefficients indicated that Monday has the highest returns volatility for the 1996 to 2000 sub-period and Friday for the 2001 to 2005 and 2006 to 2010 sub-periods. Friday has the lowest returns volatility for the 1996 to 2000 sub-period and Thursday for the 2001 to 2005 and 2006 to 2010 sub-periods.

The confidence interval analyses indicate that only the 1996 to 2000 sub-period has significant conditional variance equation coefficients. The Monday and Thursday conditional variance equation coefficients for the 1996 to 2000 sub-period were significant at the 10% confidence level while that for Friday was significant at the 1% confidence level.

The conditional variance equation coefficients for 2001 to 2005 and 2006 to 2010 sub-periods were all insignificant at the three confidence levels.

The analyses of the significance levels suggest that the day-of-the-week effect on returns volatility for the JSE Top 40 index for the sub-periods studied has disappeared in the South African stock market. However, given that the effect for Monday and Thursday was only found to be significant at the 10% confidence level, it is suggested that the effect is very weak on the two days.

# CHAPTER SEVEN: CONCLUSION AND RECOMMENDATION

# Chapter Seven: Conclusion and Recommendation

## 7.1 Introduction

The study examined and analysed whether the day-of-the-week effect exists in the volatility of the South African stock market returns using three indices – namely, the JSE Top 40, the JSE Mid Cap and the JSE Small Cap. The research also investigated whether the day-of-the-week effect has evolved, disappeared, weakened or reversed as a result of the South African stock market having matured. The study used returns data for the period January 1996 to December 2010 for the three indices. The disappearance, weakening or reversing study used the JSE Top 40 index returns data sub-divided into three sub-periods – namely January 1996 to December 2000, January 2001 to December 2005 and January 2006 to December 2010.

## 7.2 Summary of Findings and Conclusion

### *7.2.1 Data Characteristics*

With the exception of Friday for the JSE Top 40, where the mean return is negative, the preliminary analyses indicated that mean returns are positive for all three indices for the period studied.

Preliminary data characterisation indicated that the returns data of the three indices are not normally distributed. With the exception of Wednesday and Friday for the JSE Top 40, the returns are negatively skewed. The Wednesday and Friday returns for the JSE Top 40 are positively skewed.  The skewness implies that the returns have longer tails with returns concentrated to the right of the mean returns for the negative skewness and concentrated to the left of the mean returns for positive skewness.

The returns of the three JSE indices exhibit high levels of kurtosis and have fatter tails than normal distributions. The peaked-ness and fatter tails is higher for small firms and decreases with increasing size of the firm.

### *7.2.2 Day-of-the-Week Effect on Returns Volatility*

On the basis of the returns equation coefficients, for the JSE Top 40, Monday has the highest mean returns. Friday mean returns are the highest for the JSE Mid Cap and the JSE Small Cap. Tuesday is the lowest mean returns day for all the three indices.

At the 1% confidence level, the day-of-the-week effect in returns was only detected for Monday and Thursday for the JSE Top 40 index. At the 1% confidence level, the presence of the day of the week in returns was detected on Thursday and Friday for the JSE Mid Cap and the JSE Small Cap. The Monday, Wednesday, Thursday and Friday effects are present at the 5% confidence level for the JSE Mid Cap and the Wednesday effect for the JSE Small Cap. The JSE Small Cap Monday and Tuesday effects are present at the 10% confidence level only.

Thursday has the highest returns volatility for the JSE Top 40. The JSE Mid Cap and the JSE Small Cap have their highest returns volatility on Wednesday and Monday respectively. For all the indices, Fridays have the lowest returns volatility. The summaries of findings in terms of the day with the highest and lowest returns and returns volatility for the indices are shown in Table 16.

For the JSE Top 40, only Friday's conditional variance equation coefficient was significant at the 1% confidence level. The Monday conditional variance equation coefficient was only significant at 10%. The other weekday coefficients were insignificant at all three levels. On the basis of these observations, the null hypothesis is accepted for Tuesday, Wednesday, and Thursday for the JSE Top 40. The alternative hypothesis is rejected for these three days. The Friday and Monday effects at the 1% and 10% significant levels respectively were observed and, hence, the null hypothesis is rejected for these conditions for Friday and Monday.

On the basis of the findings, the null hypothesis was accepted and the alternative hypothesis was rejected for the JSE Mid Cap returns volatility. For the JSE Small Cap, the null hypothesis was rejected for all the weekdays at the 10% confidence level. However, at 1% for the JSE Small Cap the null hypothesis was rejected for Monday, Tuesday, Thursday and Friday. The alternative hypothesis was accepted under the condition of null hypothesis rejection for the JSE Small Cap.

**Table 16: Highest and lowest weekday summary for JSE Top 40, JSE Mid Cap and JSE Small Cap**

| Index | Mean Returns | | Returns Volatility | |
|---|---|---|---|---|
| | Highest Day | Lowest Day | Highest Day | Lowest Day |
| JSE Top 40 | Monday | Tuesday | Thursday | Friday |
| JSE Mid Cap | Friday | Tuesday | Wednesday | Friday |
| JSE Small Cap | Friday | Monday/Tuesday | Monday | Friday |

The analyses suggest the presence of the day of the week on the volatility of the JSE stock market returns for the JSE Small Cap. The results do not show a strong presence of the day of the week for the JSE Top 40 while there is no significance in the JSE Mid Cap index.

### *7.2.3 Variation of the Day-of-the-Week Effect During Sub-Periods*

The analysis of the returns for the sub-periods indicated that Thursday, Tuesday and Monday have the highest returns while Monday, Thursday and Friday have the lowest returns for the 1996 to 2000, 2001 to 2005 sub-periods respectively.

The day-of-the-week effect on the returns equation was detected for Wednesday and Friday at the 1% for the 2001 to 2005 sub-period and on Tuesday, Wednesday and Friday at the 5% for the 2006 to 2010 sub-period. There seems to be re-appearance of the day-of-the-week effect on the returns equation in the 2001 to 2005 and 2006 to 2010 sub-periods, which was not observed in the 1996 to 2000 sub-period.

Monday has the highest returns volatility for the1996 to 2000 sub-period and Friday for the2001 to 2005 and 2006 to 2010 sub-periods. Friday has the lowest returns volatility for the 1996 to 2000 sub-period and Thursday for the2001 to 2005 and 2006 to 2010 sub-periods. The summaries of findings in terms of the day with the highest and lowest returns and returns volatility for the three sub-period studies for the JSE Top 40 are shown in Table 17.

**Table 17: Highest and lowest weekday summary for sub-periods for JSE Top 40 index**

| Period | Mean Returns | | Returns Volatility | |
|---|---|---|---|---|
| | Highest Day | Lowest Day | Highest Day | Lowest Day |
| 1996-2000 | Thursday | Monday | Monday | Friday |
| 2001-2005 | Tuesday | Thursday | Friday | Thursday |
| 2006-2010 | Monday | Friday | Friday | Thursday |

Only the 1996 to 2000 sub-period has the Monday and Thursday conditional variance equation coefficients significant at the 10% confidence level while that for Friday was significant at the 1% confidence level.

The conditional variance equation coefficients for the2001 to 2005 and 2006 to 2010 sub-periods were all insignificant at the three confidence levels.

Since none of the coefficients for 2001 to 2005 and 2006 to 2010 were significant at any confidence level and that for Monday and Friday the conditional variance equation coefficients were significant for at least the 10% confidence level, the null hypothesis for Monday and Friday was accepted for the JSE Top 40 index for the sub-periods studied and the alternative hypothesis was rejected.

Indeed, the day-of-the-week effect on returns volatility for the JSE Top 40 index for the sub-periods studied has shown to disappear in the South African stock market. Given that the effect for Monday and Thursday was only found to be significant at the 10% confidence level, this suggests that the effect is very week on the two days.

## 7.3 Recommendations

During this study, the log return variances, where daily returns are computed as the natural logarithmic first difference of the daily closing price was used in determining the returns and returns volatility as indicated by equation 1. Based on literature, this approach provides a return measures that can be used in returns volatility modelling.

# Chapter Seven: Conclusion and Recommendation

Studying daily prices volatility using the log range variances computed using the high and low price during the day and correlate this with the day's return could be beneficial and provide additional insight and understanding of the JSE stock market.

It is recommended that a study to investigate if daily price volatility using daily high and low prices could have a correlation with the day's JSE stock market returns.

It would also be interesting to consider investigating the behavioural aspects of the day of the week effect. In other words why, psychologically, could returns / volatility differ on different days of the week.

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# APPENDICES

## Appendix A: Day of the week normal probability plots of returns (JSE Top 40)

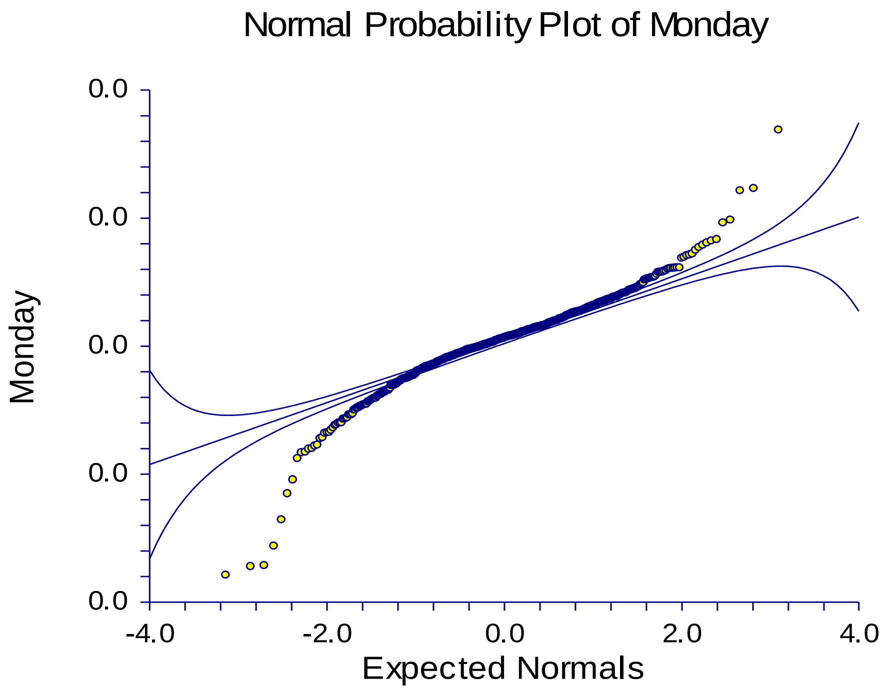


***Figure A1: Monday normal probability plots of returns (JSE Top 40)***

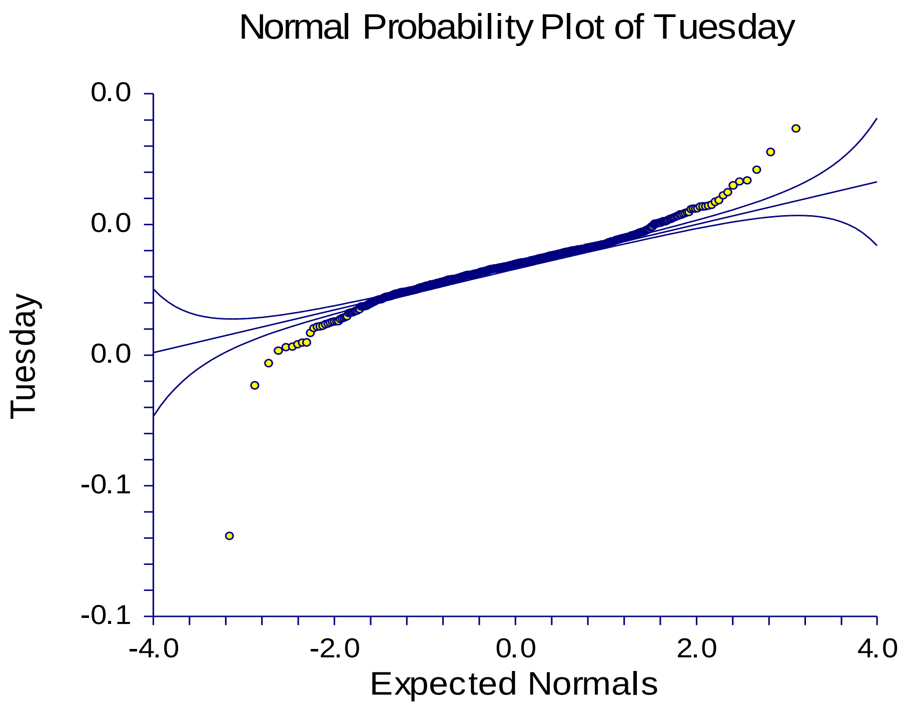


***Figure A2: Tuesday normal probability plots of returns (JSE Top 40)***

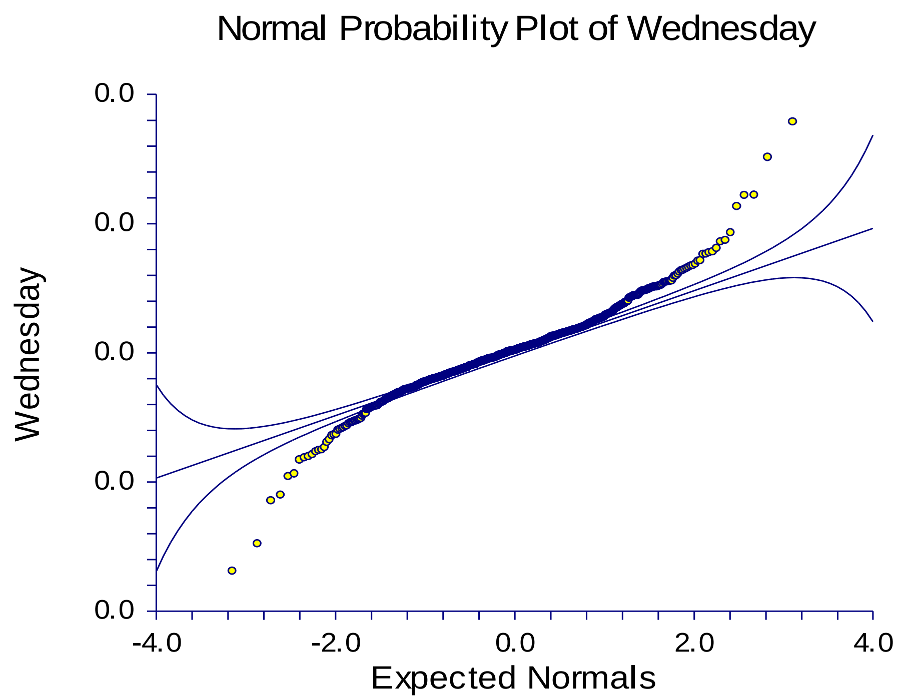


***Figure A3: Wednesday normal probability plots of returns (JSE Top 40)***

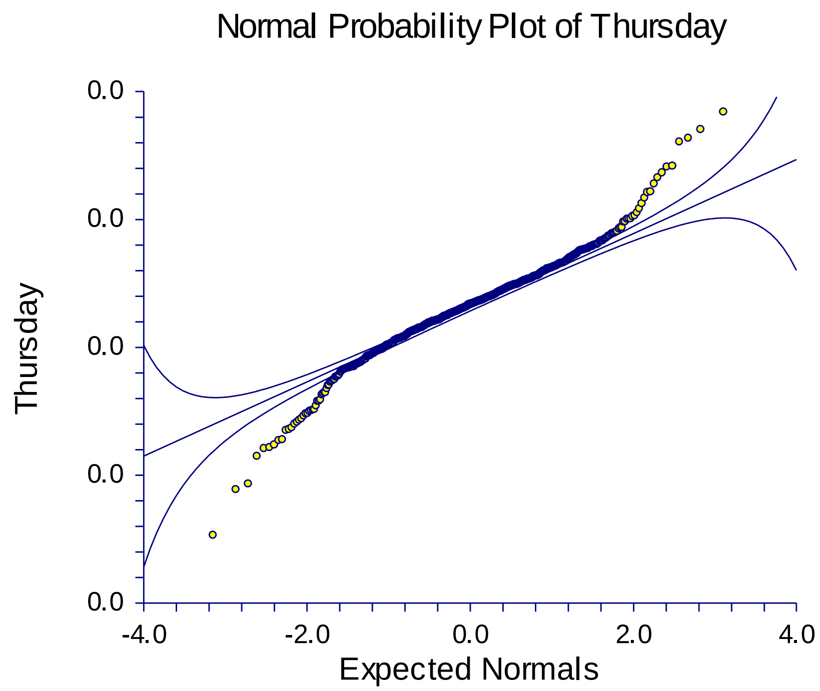


*Figure A4: Thursday normal probability plots of returns (JSE Top 40)*

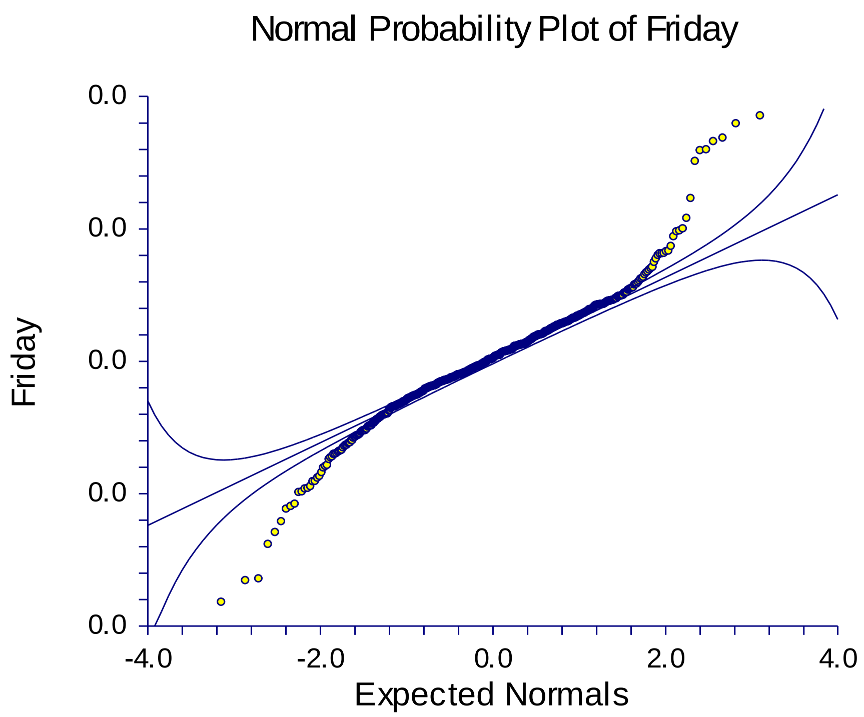


*Figure A5: Friday normal probability plots of returns (JSE Top 40)*

## Appendix B: Day of the week normal probability plots of returns (JSE Mid Cap)

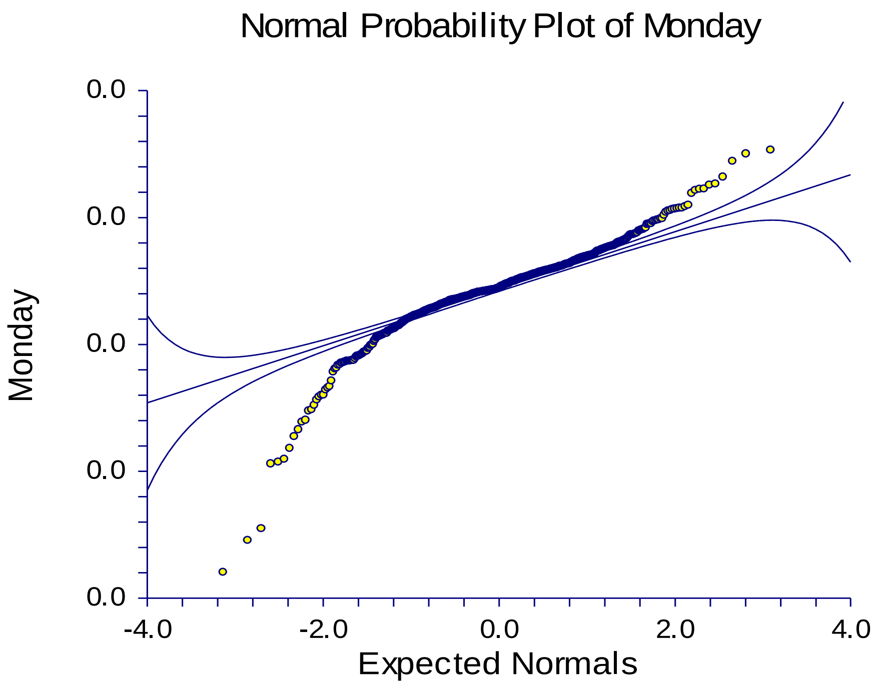


***Figure B1: Monday normal probability plots of returns (JSE Mid Cap)***

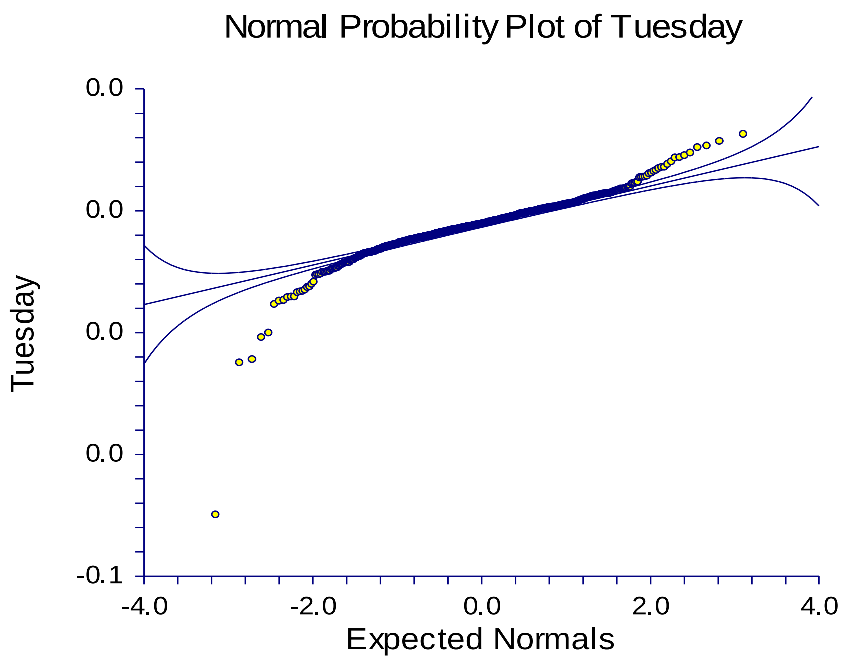


***Figure B2: Tuesday normal probability plots of returns (JSE Mid Cap)***

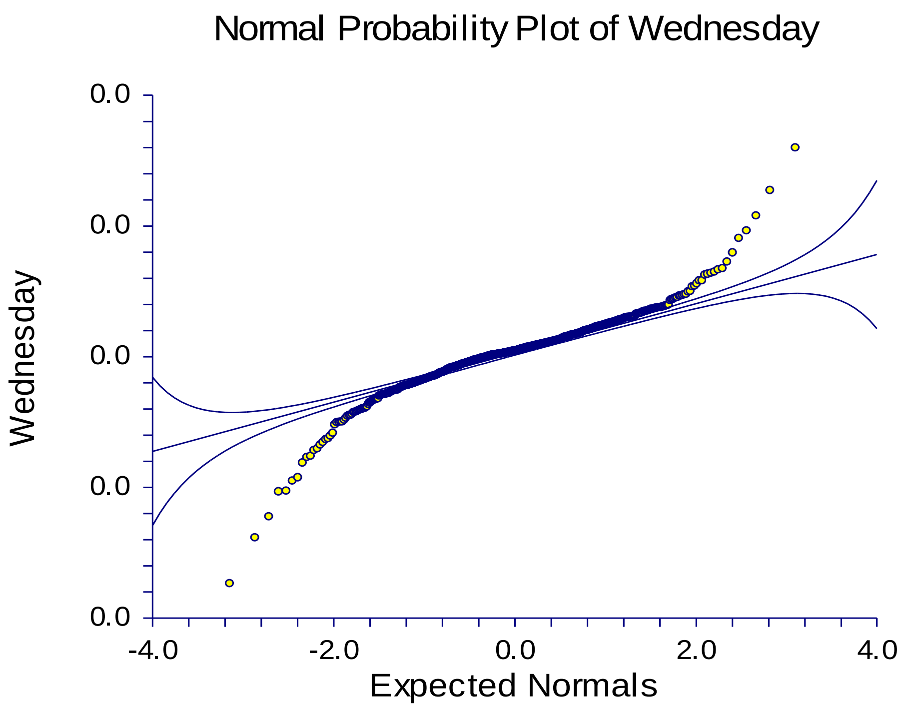


*Figure B3: Wednesday normal probability plots of returns (JSE Mid Cap)*

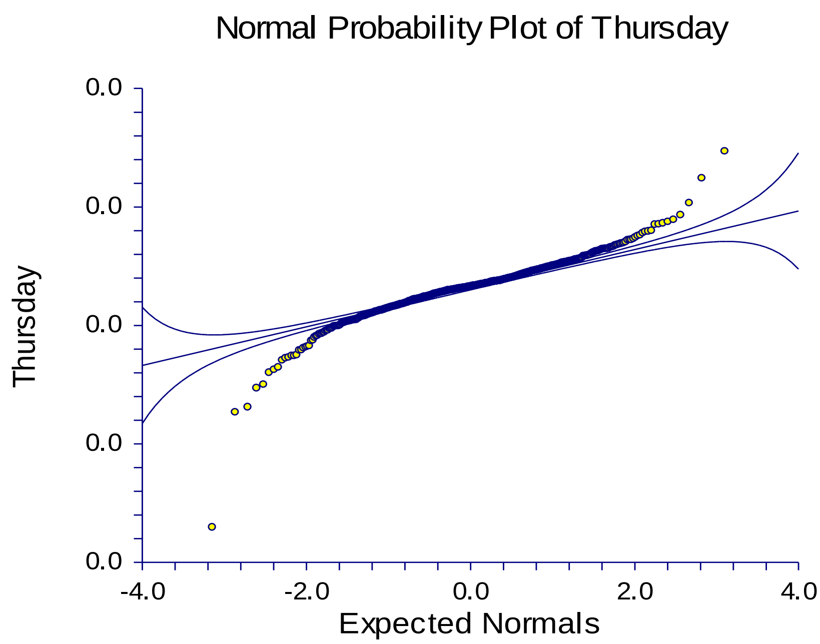


*Figure B4: Thursday normal probability plots of returns (JSE Mid Cap)*

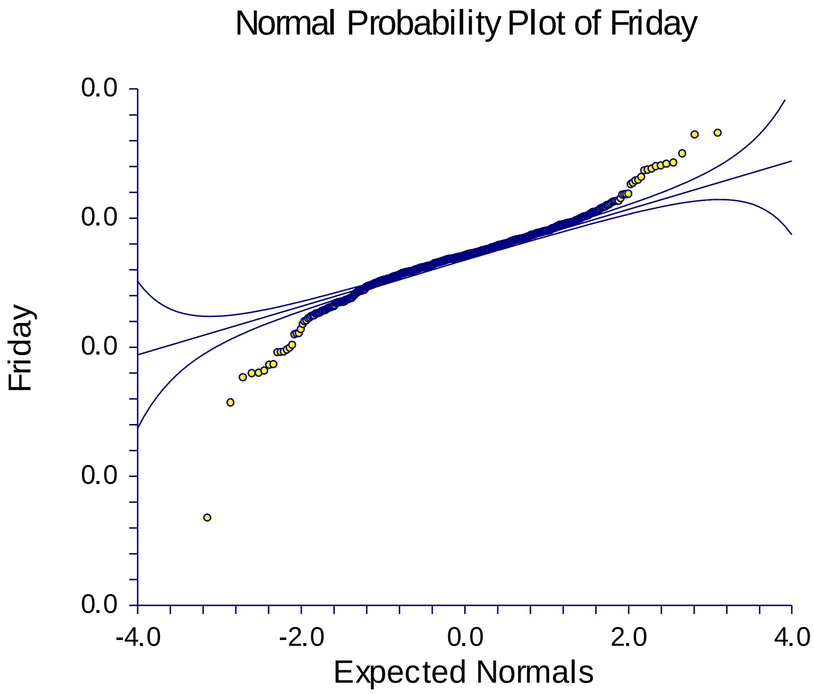


***Figure B5: Friday normal probability plots of returns (JSE Mid Cap)***

## Appendix C: Day of the week normal probability plots of returns (JSE Small Cap)

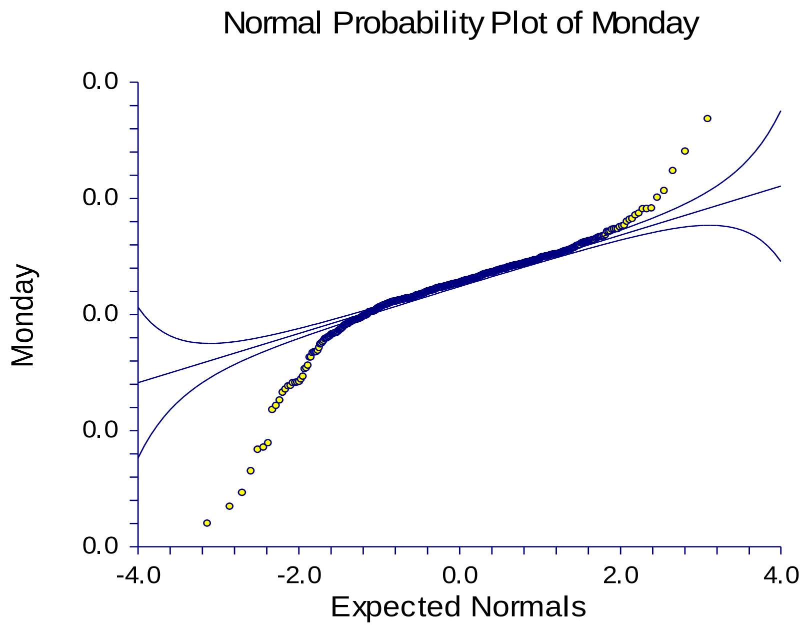


***Figure C1: Monday normal probability plots of returns (JSE Small Cap)***

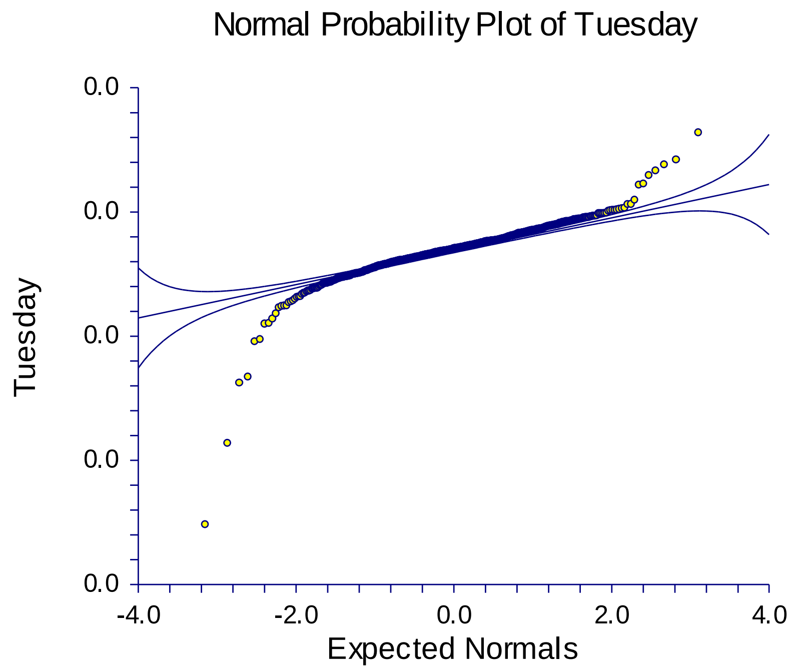


***Figure C2: Tuesday normal probability plots of returns (JSE Small Cap)***

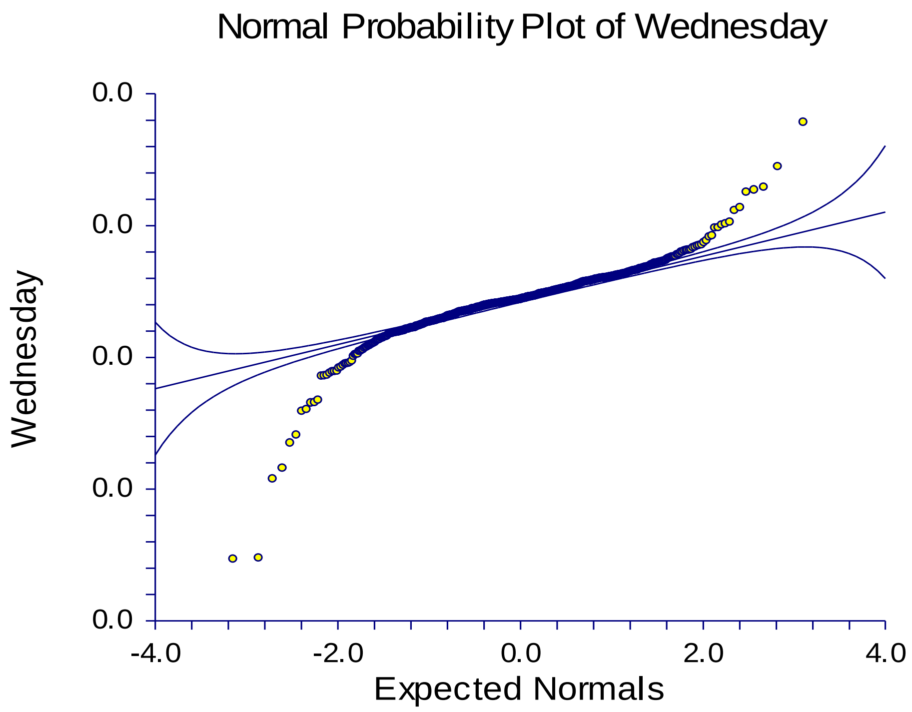


***Figure C3: Wednesday normal probability plots of returns (JSE Small Cap)***

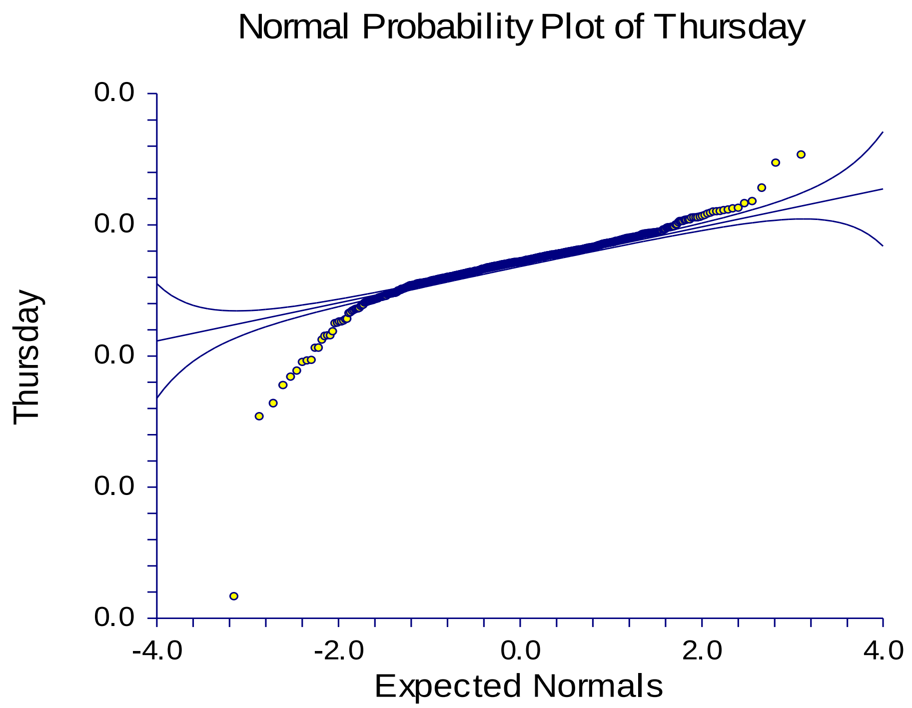


***Figure C4: Thursday normal probability plots of returns (JSE Small Cap)***

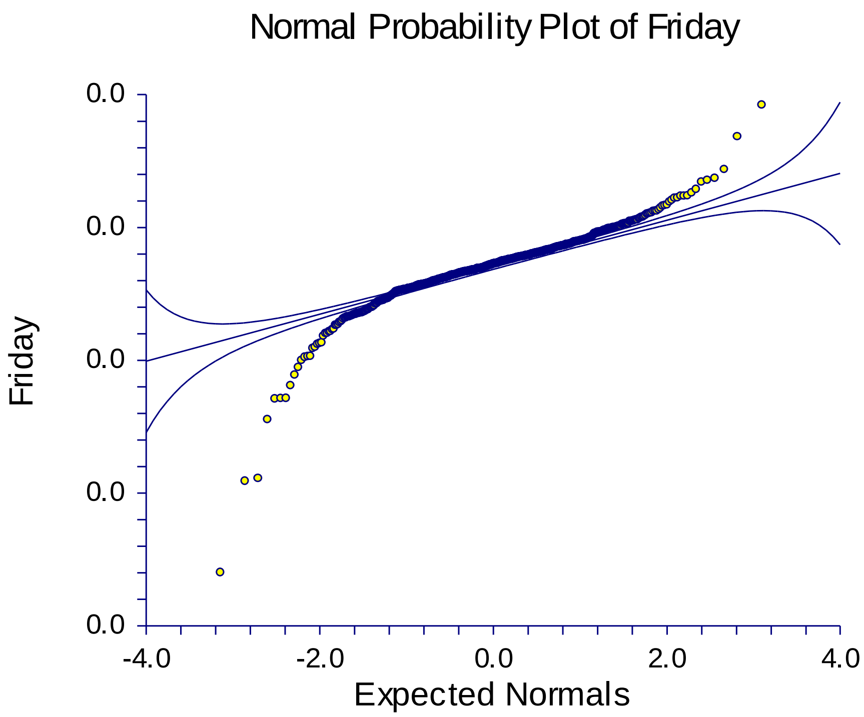


***Figure C5: Friday normal probability plots of returns (JSE Small Cap)***