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# Modeling Value-at-Risk (VaR) in a Small Sized Emerging Financial Market: Evidence from Botswana

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## Abstract

**Aim of the study:** The objective of this study is to model VaR in a small sized rapidly developing financial market in Sub-Saharan Africa which has not only served as a haven for a number of foreign investors, but also has provided the best inflation adjusted returns. This market is of profound interest given that it has received limited attention from policy analysts and previous studies.

**Methodological framework:** This study attempted to employ most of the approaches in modeling VaR, but the results of the diagnostic tests carried out showed that we could only model VaR using either the Basic Historical Simulation (BHS) or the Extreme Value Theory (EVT). Considering the fact that the Peaks over Threshold (POT) is the most preferred choice in academia and industry over the block maxima approach, we opted for the former, which also based on the EVT. The diagnostics were carried out in Eviews, while the parameters of the unconditional EVT and VaR were estimated in Microsoft Excel.

**Empirical findings:** The empirical analysis showed that the tails of the distribution were fatter than in most markets within the emerging market context. These findings do not differ much from previous studies conducted in emerging financial markets. The quantile by quantile plot also showed that the distribution in this market has heavier tails relative to the Student t-distribution. This suggests that any measure of VaR based on assumptions of normality and the Student t-distribution could distort the estimate of Value-at-Risk and have dire consequences on policy decisions. The Kupiec (1995) frequency test showed that both the EVT and BHS cannot be rejected as underlying models to estimate VaR while the Lopez (1998) frequency-of-tail-losses approach which compares and ranks both model showed that the EVT performs better than BHS.

**Significance:** This study bridged the gap in the research literature which has customarily focused on Value-at-Risk measures in “medium and large’’ financial markets in emerging economies by concentrating on a small sized rapidly developing financial market. The findings may also serve as a reference point for most policy makers operating in small sized emerging financial markets.


**Keywords**: VaR, EVT, POT, Sub Saharan Africa, policy makers, GPD

# 1. Introduction

A plethora of studies has been conducted in various contexts to determine the appropriate measure of Value-at-Risk which provides information to stakeholders to make decisions. This study, which to the best of our knowledge is the first to emerge from a small sized developing financial market aims to model Value-at-Risk (hereinafter referred to as VaR) in a small sized rapidly developing financial market in Sub-Saharan Africa which has not only served as a haven for a number of foreign investors[1], but has also provided the best inflation adjusted returns (Ikoku and Hosseini, 2008). This market is also of profound interest given that it has received limited interest from policy analysts and previous studies. Many people invest in assets with the expectation of receiving a return which is commensurate with the inherent risk (market or credit risk). Beside this motive, investors may, depending on their preference and needs, also diversify their portfolios geographically in order to circumvent risk.

From the preceding discussion, market players in several economies who wish to mitigate risk now consider other markets as viable options for diversifying their investment holdings. Over the past years, African countries sub of the Sahara have witnessed tremendous and robust economic growth, which has served as a catalyst to attract a number of foreign investors who wish to diversify their investments geographically (Ikoku and Hosseini, 2008). To buttress this argument, a study by De Vita and Kyaw (2008) cited remarkable changes in global economic policies, capital market development, stable political environment, changes in capital control policies and banking supervision as some of the main factors which have accounted for the rapid investments in the African countries sub of the Sahara.

Most of these Sub-Saharan African financial markets have also demonstrated strong signs of rapid growth in terms of market capitalization, product and market development, systems automation, listings and trading activities which have also served as an inducement and a pull factor (see Ikoku and Hosseini, 2008). The Botswana Stock Exchange (BSE) for instance is currently in the process of introducing platinum Exchange Traded Fund (ETF) and Global Depositary Receipts (GDR), an initiative which is expected to provide local and foreign

[1] A United States Foreign Policy Magazine has ranked Botswana as the best destination in the world for foreign investors. Government spokesperson, Jeff Ramsay told Gabz Fm News that last year Botswana came in second to Hong Kong in the Baseline Profitability Index survey, BPI. The BPI report evaluated a hundred and twelve countries around the world based on factors that include economic growth, physical security, corruption, and exchange rates to determine the investment value of an economy based on the security and rate of return on investment.

investors an opportunity to invest in physical platinum and make cross border investments without restrictions[2].

In spite of these developments, emerging financial market sub of the Sahara have historically been described as high risk investment regions, characterized by low trading volumes, high illiquidity, lack of asset classes to diversify inherent risks, high and skyrocketing inflation, exchange and interest rates (see Tolikas, 2011; Maghyaren and Al-Zoubi, 2006). Though these features tend to define the majority of financial market sub of the Sahara, there are quite a number of them whose stable policies have attracted countless international investors (see Ikoku and Hosseini, 2008)

In today's world of varying economic conditions, investors are not only concerned with cash flows from their investment holdings, but also the amount they could lose in the event of a normal or extreme market condition in the economy. Many participants in the financial markets therefore seek answers to questions like: how much, when and what is the probability that this amount of value could be lost as a result of an unfavorable market or economic condition? Market players operating in some of these highly volatile African financial markets also often seek strategies which can help mitigate their exposure to the different forms of market risk. In order to effectively hedge their positions, these investors need not know only how much they stand to lose in the event of adverse market conditions, but also the circumstances under which such losses may take place.

With globalization on the ascendency and the deregulation of financial markets, many techniques ranging from basic to sophisticated like variance, standard deviation, gap, duration, scenario analysis, Value-at-Risk, credit risk metrics, expected shortfall among others have been developed to determine the amount an investor shall forego on an investment in the event of an adverse or normal market condition in the future state. For instance Sinkey (1992) developed a gap analysis model to capture interest rate risk exposure of financial institutions; while Fabozzi (1993) and Tuckman (1995) modeled duration analysis as a measure of interest rate risk exposure. Some of these methods do not only fail when it comes to predicting with precision the circumstances under which a worse scenario may occur, but are also considered

[2] http://www.sundaystandard.info/article.php/email.php?NewsID=15143

as incoherent risk measures (see Dowd, 2005). The most widely used of these statistical techniques, which addresses a broad spectrum of risk related issues for investors and policy makers, is Value-at-Risk (VaR).

VaR is considered as the minimum or maximum[3] loss expressed in monetary terms with a given confidence level over an investment horizon. The key point in the aforementioned definition is that stakeholders are concerned with the value they could lose due to adverse economic conditions over an investment horizon with a degree of certainty. Degiannakis, Floras and Livada (2012) point out that for many risk models that are built on forward looking assumptions, the outcome from such models could be used to manage risk effectively since these models convey the magnitude of the market risks of portfolios to market actors. Thus policy makers place a premium on the accuracy of VaR measures because it provides the basic information required to allocate resources effectively and efficiently. For instance, based on the estimate of VaR, may be able to decide how best they can manage firm risk using derivative or other risk management tools at their disposal.

Though the concept of VaR and other key risk measures give management and stakeholders an insight on what strategies to pursue to mitigate losses arising out of unstable market conditions, policy makers and market participants often face a dilemma regarding which technique to employ to achieve consistent and accurate results in the markets in which they function (Hopper, 1996; Hull and White, 1997; Duffie and Pan, 1997; Jorion, 1997; Dowd, 1998). Moreover, the literature on risk measures is also barren when it comes to specifying the model specification that will thrive in a particular market.

More so the Basel Committee (1996, 2004) on banking supervision stipulates that institutions could develop their own internal models to capture Value-at-Risk for the next holding period. The problem however with this approach is that financial institutions which fail to accurately develop models to predict future losses are penalized severely with a higher multiplicative factor (see Mapa and Suaiso, 2009). This punitive measure aims to prevent institutions from sub optimally allocating resources to mitigate future losses which stem from deploying inaccurate models to estimate VaR. A review of previous studies in various contexts showed

[3] provided no tail event occurs

that except for this small sized emerging financial market, countless models have been developed in various financial markets in Asia, North Africa, Eastern Europe and Latin America to assist firms which intend to develop their own internal models to capture Value-at-Risk (see Maghyaren and Al-Zoubi, 2006; Tolikas, 2011; Onour, 2010; Fernandez, 2003).

However, the Botswana market considered as a small sized emerging financial market in the developing market bracket (Smith, Jefferis and Ryo, 2002), has received limited attention not only from policy analysts, but also previous studies which focused on risk measures in Sub Saharan African financial markets. The low interest in this market could stem from the premise that the medium and larger financial markets are often considered as good proxies for the entire financial markets in Africa and as such findings of studies conducted in these markets could be generalized to the other financial markets in the Sub region. In most instances the findings of studies on risk measures in some Sub-Saharan African financial markets are applied by policy makers and other participants in this market without any modification. The practice of adopting findings to this market has placed a huge challenge for policy makers who are unsure regarding which recommendation on VaR should be applied to measure risk in this financial market. This study is therefore posited to address this basic problem by modeling VaR for this small sized rapidly developing market in Sub Saharan Africa.

The study sample consists of daily equity index from the Botswana Stock Exchange, and spans a time period from January 3, 2002 to December 31, 2009 which is further split into three 5-year rolling sub-sample periods namely: sample 1, sample 2 and sample 3. VaR was estimated for the out-of-sample one year test periods which we called: pre-crisis, crisis and post-crisis. We selected this sample frame to capture the global financial crisis because of the popular belief that extreme events often lead to abnormal returns that are paramount in the decision making process of market players. We also estimated VaR using the Basic Historical Simulation approach which does not make any restrictive assumptions regarding the underlying data and the Extreme Value Theory which depends on distributional assumptions.

The main contribution of this study is in two fold. Firstly, it adds significantly to the existing literature by providing a measure of VaR from a small sized rapidly growing financial market in Sub-Saharan Africa; and thus bridges the gap in research literature which has mostly focused on large developed financial markets in emerging economies. The study will also serve as a reference point for actors in small sized emerging financial markets who may face challenges regarding which technique will be the best estimator of any risk measure (VaR).

The organization of this study is as follows: section 2 reviews existing literature on VaR while section 3 discusses the preliminary analysis and the methodological framework we adopted. In section 4 we present the results of the data analysis and we summarize the findings as well as proffer recommendations in section 5.

## 2. Literature Review

This section reviews extant literature on VaR under the following thematic areas: the concept of VaR; techniques/measures of VaR; backtesting and validation approaches.

### 2.1. Concept of VaR

The principles enshrined in the conservation of value theory seems to be the overarching objective of firm policy decision making since managerial incentives have traditionally been tied to firm performance. The concept of risk management is beginning to gain ground, both in practice and literature due to the behaviour and assumptions that investors are risk averse and will attempt to implement strategies to mitigate future losses. Consequently, market participants are moving from brick-and-mortar investment practices to pursuing novelty policies which reduce their overall exposure to risk. After a pioneering study by JP Morgan (1996), VaR was developed as a standard measure of risk for both financial and non-financial firms on which managers can base their decisions.

VaR is defined as the minimum loss, such that the probability of a future portfolio loss exceeding the minimum value is less than or equal to one minus a confidence interval (Dowd, 2005). The definition which is represented in equation (1) below shows that VaR depends on two key parameters-the holding period or the length of time an investment is held before it is liquidated and the confidence interval which measures how certain we are regarding the estimate of VaR.

$$VaR = min\{\ell : \Pr(L > l) \leq 1 - \alpha\} \qquad \textbf{(1)}$$

Dowd (2005) notes that these parameters are arbitrarily selected and the choice depends largely on the purpose of VaR. Dowd (2005) argues further that if the objective is to backtest or validate a model, then a shorter holding period could be used while a high confidence level could be selected for the same purpose.

VaR as a standard statistical measure of risk has been extensively applied in various markets to capture how much an investor may lose in the next holding period with a degree of certainty. For instance, Crouchy, Galai & Mark (1998, 2001) and Burchi (2013), note that

VaR models are employed by the bank regulators to determine bank regulatory capital requirements. VaR could also be used by senior management for reporting firm performance (see Jorion, 2001), disclosure purposes (see Moosa and Knight 2001) and to set overall risk targets (see Kuruc and Lee, 1998). In spite of the usefulness of VaR models, Beder (1995); Marshall and Siegel (1997) point out that VaR estimates could be less useful if the models yield different results. More so, VaR does not provide information about the losses beyond the confidence level, thus making it difficult for firm managers to protect their position against larger losses (see Taleb, 1997; Danielsson, 2009; Basak & Shapiro, 2001).

Since the implementation of the famous '4.15 report' of JP Morgan (see Dowd, 2005), which led to the subsequent development of VaR, a number of methods has been developed to estimate VaR. The methods discussed in the subsequent section of this review include, but it is not limited to parametric and nonparametric approaches to estimating VaR.

## 2.2. Measures of VaR

This subsection discusses the standard measures to estimating VaR used in various studies. The main non-parametric approaches, we discussed here include the Basic, Age Weighted, Volatility Weighted Historical Simulation while the parametric covered the Normal and Student-t distributions. In addition, we reviewed the Extreme Value Theory (EVT) method to estimating VaR.

### 2.2.1. Non-Parametric Methods

The non parametric methods estimates VaR without making any assumption regarding the distributional property of the asset returns or data; and it is based on the underlying premise that future losses will exhibit similar properties to historical data. The most commonly discussed methods in the literature are the Basic, Age Weighted and Volatility Weighted Historical Simulation.

#### *2.2.1.1. Basic Historical Simulation*

The Basic Historical Simulation (BHS) approach, according to Dowd (2005) uses the empirical loss observation to estimating VaR. This method assigns essentially the same weight to each historical loss observation. Following from equation (1) and extending the argument we would expect the estimated VaR in the sample of observed losses to be equivalent to:

$$(1-\alpha)N+1, \qquad \textbf{(2)}$$

Where N denotes the sample size

For example, in a sample of 200 observed losses with a confidence interval of 99%, we would expect a VaR to be equivalent to the third largest loss following from the equation (2) specified above.

A basic shortcoming of the Basic Historical Simulation approach is that it assumes that all the loss observations in the sample have an equal chance of occurring in the future. Thus new and old loss observations would be assigned the same probability given the belief that there is an equal chance of occurrence. However, in reality current rather than the older observations do have a greater impact in predicting future data, and assigning equal weight to loss observations would make VaR estimates unresponsive to extreme events such as the global financial crisis (see Shimku, Humpheys and Pant, 1998; Pritsker, 2001)

#### *2.2.1.2. Age-Weighted Historical Simulation*

The Age Weighted Historical Simulation takes into consideration the ‘‘weighting structure’’ shortfall of the Basic Historical Simulation approach. This approach to modeling VaR asserts that current data plays an integral part in modeling future observations and as such should be assigned more weight than older loss observations (Boudoukh, Richardson and White, 1998). The Age Weighted Historical approach estimates VaR by computing the weights or probabilities which Dowd (2005) argues, decreases exponentially from the most current to the oldest loss observation. The observations are then sorted in ascending order while the weights are kept constant, thus ensuring that the largest other than the least loss observations are assigned higher weights.

The main drawback of this approach is that it is based on the assumption that volatility is constant and as such it does not reflect new market conditions (see Dowd, 2005). In effect this like the Basic Historical Simulation is not responsive to new information that arrives to the market. More so, estimates of VaR are likely to be low during tranquil periods and vice-versa (Pritsker, 2001).

#### *2.2.1.3. Volatility-Weighted Historical Simulation*

The underlying premise for this approach as Dowd (2005) puts it and which Brooks (2008) refers to as volatility clustering or pooling stems from the fact that if volatility is higher or lower today, then it is likely to exhibit the same property in the next holding period. Though this approach estimates VaR following the procedure discussed in the Basic Historical approach, the empirical loss observations are rescaled using values estimated by volatility models such as Generalized Autoregressive Conditional Heteroscedasticity (GARCH) or Exponential Weighted Moving Average (EWMA). The losses are rescaled following the approach specified below:

$$l_T^* = \frac{\sigma_{T+1}}{\sigma_T} * l_T \quad \textbf{(3)}$$

Where: $l_T^*$ = Scaled Losses

$l_T$ = Actual Losses

$\sigma_T$ = Current Volatility

$\sigma_{T+1}$ = Forecasted Volatility

Volatility is estimated using either the standard GARCH (1,1) or the EWMA defined in equation (4&5) respectively:

$$\sigma_T^2 = \omega + \alpha * \varepsilon_{T-1}^2 + \beta * \sigma_{T-1}^2 \quad \textbf{(4)}$$

$$\sigma_T^2 = (1 - \lambda) * \varepsilon_{T-1}^2 + \lambda * \sigma_{T-1}^2 \quad \textbf{(5)}$$

Where: $\omega$ = intercept term

$\alpha$, $\beta$ = coefficients ($\alpha$+$\beta$< 1, for stationarity)

$\lambda$ = constant (0.94 from RiskMetrics)[4]

$\varepsilon_{T-1}^2$ = the error term

The caveat with this approach as pointed out by Engle (1982) and further buttressed by Brooks (2008) is that considering whether to incorporate time varying volatility into any analysis requires firstly that an Autoregressive Conditional Heteroscedasticity (ARCH) effect test is conducted to determine if the data series exhibits features of time varying volatility or whether the residuals are serially autocorrelated.

This approach considers volatility in modeling VaR, which the Basic Historical and the Age Weighted Simulation approaches hardly factor in the estimation of VaR. For example Sinhua and Chamu (2005) conducted a study using two Historical Simulation and Volatility Weighted methods to compute VaR using extreme data from the Mexican market. The finding of this study show that the Volatility Weighted Historical Simulation performs better compared to the two historical simulations. This finding was corroborated by Liu, Wu and Lee, (2004); Obi and Sil (2013); Degiannakis et al (2011); Halbleib and Pohlmeier (2011). The main setback of this approach is that the rescaled loss observations are larger than the original losses (Dowd, 2005).

### 2.2.2. Parametric Methods

The parametric approaches to estimating VaR are based on the moments of a distribution. These moments refer to the mean, standard deviation, skewness and kurtosis of a distribution. The main approaches are underpinned by normal, Student-t and lognormal distribution.

#### *2.2.2.1. Normal Distribution*

The pioneering works of JP Morgan (1996) which formed the basis of the standard VaR and which has been adopted by most regulatory agencies such as the Basel Committee assumed that asset returns were normally distributed (see Obi and Sil, 2013; Burchi, 2013; Los, 2004; Chrisiansen, 1999). The normal distribution approach assumes that an asset's distribution is

[4] Morgan Guaranty Trust Company (1996)

characterized by the first and second moments which are the mean and standard deviation. Under the parametric approach, VaR is defined in equation (6) as the sum of the mean of losses and the product of the standard deviation and critical value.

$$VaR = \mu + \sigma * Z_\alpha \tag{6}$$

The mean and variance parameters may be estimated by taking the maximum likelihood mean and variance estimators while the critical value or probability density function which is often read from distribution tables.

The main shortfall of this approach as noted by Dowd (2005) and Brooks (2008) is that this method assumes that volatility is constant and as such does not account for the "stylized fact" property of financial asset returns. The way forward as pointed out in numerous studies (Brooks, 2008; Bollerslev, Chou and Kroner, 1992) is to use models which can accommodate time varying volatility as discussed in the volatility weighted historical simulation approach. We therefore define VaR, which is shown below as conditioned upon a time varying parameter which is the volatility.

$$VaR = \mu + \sigma_{t+1} * Z_\alpha \tag{7}$$

This approach also does not consider the heaviness of the tails of the distribution in modeling VaR and it suffers significantly from low power of the test (see Christianssen, 1999). Nielson's (2009) seminal work on measuring and regulating extreme risk revealed that measuring risk based on normality assumptions could affect management decision making since resources could sub optimally be allocated to manage exposure to risk.

***2.2.2.2. Student-t Distribution***

VaR can also be estimated under the assumptions that the returns of an asset or index does not follow a normal distribution which means that the distribution could be described using four key parameters-mean, standard deviation, kurtosis and skewness. This is not to say that a normal distribution is also not characterized by these parameters, but under normality the third and fourth moments will usually have a coefficient of kurtosis of 3 and it is always considered to be symmetrical about its mean. In order to accommodate returns with excess kurtosis, the Student-t distribution which often contains a third parameter referred to as degrees of freedom is introduced to control for excess kurtosis.

More so empirical studies conducted by Bollerslev et al. (1992); Fama (1965); Loretan and Philips (1994); Muller, Dacorogna and Pictet (1998); Levich (1985) Duffie and Pan (1997) suggested that financial asset returns are skewed, leptokurtic and asymmetrical. Most of these authors used the term "stylized facts'' to describe the properties of financial asset returns, suggesting that any measure of VaR under the assumption of normality could lead to distortions in estimates. A key explanation offered for the "stylized fact" property is that information inefficiency issue, political, social and liquidity problems in emerging markets cause the tails of the distribution to be heavy tailed relative to the developed markets (see Harris and Kucukozman, 2001; and Tolikas, 2011).

A number of VaR studies conducted in emerging markets offered the same conclusion with regards to the feature of financial assets (see Susmel, 2001 in Latin America; Jondeau and Rockinger, 2003; Angelidis & Benos, 2005 in emerging and developed markets; Suleman, Hamid, Shah and Akkash, 2010; da Silva and Mendes, 2003 in the Asian markets; Maghyaren and Al-Zoubi, 2006; Tolikas, 2011 in Middle East and North African countries). VaR studies conducted developed countries and which were based on the assumptions of non-normality were carried out by Gettinby, Sinclair, Power and Brown (2006) and Tolikas and Gettinby (2009) in three information efficient markets-USA, UK and Japan.

The Student t-distribution like any other parametric method to estimating VaR has its own drawbacks that raise a number of question marks regarding its reliability and validity. Most of the empirical studies mentioned in the preceding sections and which provide some discussion on modeling VaR underpinned by the Student t-assumption failed to succinctly highlight the limitations of the approach to readers. Evans, Hastings and Peacock (2000) and Dowd (2005, 1998) point out that the Student t-distribution cannot be considered as stable since "the sum of two or more random variable is not necessarily distributed as a t-variable itself''. Another criticism leveled against this method and other parametric approaches is that estimates of VaR are not consistent with EVT especially when high or low confidence levels are applied (see Dowd, 2005; Huschens, 1997; Diebold, Schuermann and Stroughair, 2000).

### 2.2.3. Extreme Value Theory

Another parametric or semi-parametric method of computing VaR which improves on the setbacks of the previous discussed method is via the Extreme Value Theory (EVT), which models VaR by concentrating on the large losses or tails of distribution (see Dowd, 2005, 1998; Fernandez, 2003). Even though the literature suggests that there are two notable approaches both of which leads to the same conclusion to estimating VaR, the Peaks over threshold (POT) seems to be the most preferred choice in practice and academia. This is partly due to the frequently pointed out setback that the Generalized Extreme Value (GEV) distribution which is the other approach focuses on only the maximum loss in the observation; and therefore leads to the loss of vital information which could be applied in the modeling process. The POT which was developed in response to the criticisms leveled against the block maxima or GEV approach considers losses beyond an arbitrary chosen threshold value, but there is a trade off as too many or fewer observations could be factored in the modeling of VaR.

The extreme value theory is taking precedence in the finance literature in recent years as it focuses on extreme events (see Uppal and Mangla, 2013; Hotta, Lucas, and Palaro 2008; Gencay and Selcuk, 2004a, b; Bali and Neftci, 2001; Gilli and Kellezi, 2006). Given that these events have a higher impact not only on capital markets, but also other fields of discipline, a number of studies have been dedicated to examining the concept in greater detail. Goldberg and Giesecke (2004) noted that the prevalence of extreme events in financial markets has seriously affected the performance of various models which work effectively under normality assumptions.

LeBaron and Samanta (2006) investigated EVT and fat tail theory in a number of equity markets in various geographic zones and their finding showed that the distribution of asset returns in emerging economies was fatter than the developed markets. Though their study was not conclusive on the method that could be employed in either developing or industrialized markets, they did point out some caveats for policy makers in these markets. In the study of Harmantzis, Miao and Chien (2006) on modeling risk measures for distributions with heavy tails, it became evident that models built on extreme value theory seem to perform better than others; and asset returns tend to exhibit leptokurtic and non symmetrical properties. Though this paper provided empirical evidence in support of the assertions mentioned the findings failed to indicate the circumstances under which a particular measure may work. Will VaR measures underpinned by EVT perform better in all markets?

## 2.3. Backtesting of VaR Models

Any model once developed needs to be validated for errors, consistency, and accuracy among a number of indicators before it is implemented practically. Risk management models in this regard are also tested for evidence of the aforementioned features. The two most common approaches to validating a model as mentioned by Dowd (2005) are the Kupiec (1995) frequency based and Christoffersen (1998) test. Even though these models yield identical results they are distinct in the manner in which they approach model validation.

### *2.3.1. Kupiec (1995) Frequency Test*

The Kupiec frequency test considers the number of actual with the expected frequency of VaR violations or exceedances (Kupiec, 1995). A VaR violation or exceedance could be conceived to occur when the value of the loss in the out-of-sample exceeds the VaR estimated for the test period. The Kupiec frequency test compares the probabilistic results with the significance level of the test in order to make a decision regarding whether the underlying model should be rejected or not. This test primarily suffers from the low power of the test (see Lopez, 1998).

### *2.3.2. The Frequency-of-Tail-losses (Lopez I) Approach*

Backtesting a model also involves comparing and ranking models in order to determine which model is considered superior (Dowd, 2005). Dowd (2005) argues that this ranking and comparison model does not suffer from “low power of standard frequency test is basically a forecast evaluation method which provides a model with a score in terms of a loss function which is then used to rank the models.” The QPS takes on a value between zero (0) and two (2), and the closer this value to zero (0), the better the model. This approach to backtesting a model does not specify in statistical terms, whether an underlying model performs better or not.

## 3. Preliminary Data Analysis and Methodology

In this section, we discuss the sample data, the preliminary data analysis, we carried out and the methodology we employed.

### 3.1. The Sample and Preliminary Data Analysis

This study employs a daily market capitalization equity index, which was obtained with permission from the Botswana Stock Exchange (referred to as BSE Index hereinafter), and spans the period January 3, 2002 to December 31, 2009. In order to model VaR to reflect the market risk before, during and after the global financial crisis, we split the entire sample into three 5-year sub samples of a 12-month rolling window, namely: sample 1 which covered the period 2002-2006; sample 2 spanned the length 2003-2007 while sample 3 captured the period 2004-2008. In this case each year ahead served as the holding period for the VaR estimate as well as the test or out-of-sample period. Therefore, we had 2007, 2008 and 2009 as the test periods for the pre-crisis, crisis, and post-crisis test periods respectively. The aim of splitting the entire sample into three sub sample periods is to facilitate the evaluation of how the various VaR measures performed before (normal market condition), during (extreme market condition) and after the global financial crisis (post extreme market condition).

Though a study of this nature must consider a large sample size in order to make accurate inferences, we chose to use data from the Botswana Stock Exchange following from Smith et al.'s (2002) classification of the African Stock Markets; and a modified version of the expected utility maximization trade off theory that foreign investors are more likely to participate in markets where the risk associated with their investments is minimal, and the return is somewhat higher; and also on the feature of small sized emerging markets which have demonstrated rapid growth in terms of development.

As suggested by Dowd (2005), we conducted an initial preliminary analysis by visually inspecting if the data under consideration. The aim is to examine if the sample data "looked right or had a series of question marks''. In the course of this exercise we took out a number of non trading days[5] which had the tendency to affect the computation of lognormal returns, the moments of the distribution and the subsequent estimation of VaR (see Campbell, Lo and Mackinlay, 1997). We also carried out this exercise to ensure continuity in the data set.

[5] No trading activities during holiday periods

### *3.1.1. Descriptive Statistics*

The summary statistics for the sample as can be seen in table 1 below and appendix A1 show that the total observation for the period 2002-2009 was 1975. The average return for the periods under consideration was .000548 with a maximum and a minimum of 0.095056 and -0.033402 respectively. The lognormal mean which is close to zero confirms the suggestion in the literature that lognormal returns must exhibit a "white noise'' process (see Brooks, 2008). Even though the mean return of the BSE index relative to the averages in some of the largest and medium sized African markets used as samples in the studies conducted by Tolikas (2011) and Maghyereh and Al-Zoubi (2006) seemed to be lower, the standard deviation of the former could be considered to be significantly lower thus confirming the findings of Ikoku and Hosseini (2008) that BSE provided the best inflation adjusted returns in Sub-Saharan Africa.

The kurtosis which is basically considered as the best descriptor of the properties of the tails of a distribution shows a value of 74.4 which is considered higher than the results in the studies conducted by Maghyereh and Al-Zoubi (2006), Susmel's (2001) and Tolikas (2011) in some medium and large markets in Africa and Latin America with approximately the same sample lengths. The finding, which is similar to the empirical evidence of LeBaron and Samanta's (2006) study, therefore suggests that small sized developing markets do not only have fatter tails than the developed economies, but also the supposedly "large markets" in the emerging economy brackets. The heaviness of the tails in this market could best be explained from Tolikas (2011), Harris and Kucukozman (2001) study that liquidity and information inefficiency issues account for such "stylized fact'' properties in emerging markets. This finding that the BSE index exhibits leptokurtic properties also corroborates previous studies conducted by da Silva and Mendes' (2003) on the Asian market, Jondeau and Rockinger's (2003) in some developed and emerging markets and Suleman et al. (2010) in some Asian pacific markets.

It is also interesting to note that the positive skewness of 4.26 differs significantly from Tolikas' (2011) study in which the large markets examined in Sub-Saharan Africa showed that even though the returns were leptokurtic, they were negatively skewed. The skewness as we mentioned earlier could influence the modeling of tail events and the results therefore indicate that in modeling VaR underpinned by EVT, we must consider the right and not the left tail. The final descriptive test which is the Jarque-Bera test statistic also confirms that at a p-value of 0.0000, the assumption of normality is rejected in the market under consideration. The findings of the summary test statistic point out two important warnings that going forward, any estimate of VaR, which relies on the assumption of normality will not only underestimate VaR, but could have dire effects on the decisions of policy makers. The caveat with this finding is similar to the empirical evidence of Lechner and Ovaert (2010) who suggested that various VaR techniques other than normality assumptions should be considered when the distribution properties of the returns are leptokurtic and fat tailed.

**Table 1: Descriptive Statistics for the BSE Index Log Returns**

| Statistic | Entire Sample: 2002-2009 | Sample 1: 2002-2006 | Sample 2: 2003-2007 | Sample 3: 2004-2008 |
|---|---|---|---|---|
| Number of Observations | 1975 | 1230 | 1231 | 1245 |
| Mean | 0.000548 | 0.000752 | 0.000989 | 0.000831 |
| Median | 0.00000730 | 0.000147 | 0.000221 | 0.000198 |
| Maximum | 0.095056 | 0.095056 | 0.095056 | 0.095056 |
| Minimum | -0.033402 | -0.029616 | -0.029616 | -0.033402 |
| Standard Deviation | 0.005172 | 0.004989 | 0.005377 | 0.005655 |
| Skewness | 4.262369 | 6.234284 | 5.773184 | 4.8452815 |
| Kurtosis | 74.44311 | 114.5080 | 92.466501 | 78.55317 |
| Jarque – Bera | 426006.6 | 645212.2 | 417389.7 | 301003.7 |
| Probability* | 0.000000 | 0.00000 | 0.00000 | 0.00000 |

*Null hypothesis as per the description in Brooks (2008) for standard normality test is that the distribution of the series is symmetric and mesokurtic. The probability of the JB test shows that we reject the null assumption of normality at the conventional significance test levels of 1% and 5%

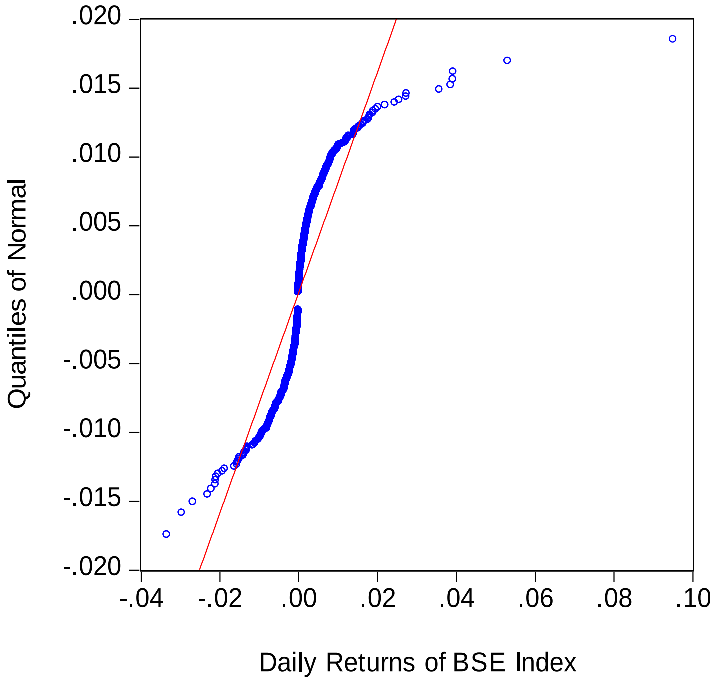
A look at the results in the table 1 above and appendix (A2, A3 & A4) also shows that the standard deviation was higher for sample 3 compared to the other sub samples which did not consider observations during the global financial crisis. The third and fourth moments (skewness and kurtosis, respectively) of the distribution during the sub-sample periods under consideration also confirms the general overview we had earlier that the tails of the BSE index were positively skewed and leptokurtic thus providing an in depth picture regarding the assumptions we make in modeling VaR.

### *3.1.2. Testing the Goodness of Fit*

We investigated the tail behaviour of the sample data, using the quantile- quantile (QQ) plot, a popular tool used in conducting exploratory data analysis. According to Ren and Giles (2007), a QQ Plot is a graphical technique which is used to check whether a sample data fits a known distribution. This method essentially compares the quantiles of the empirical distribution function with the quantiles some desired reference distribution. If the empirical data comes from the reference distribution, then the plot will be approximately linear while deviations of the data points from the straight line would imply that the sample comes from a different distribution. For a normal QQ plot, the points on a QQ plot should have an S-shape if the sample data has heavy tails compared to the normal distribution.

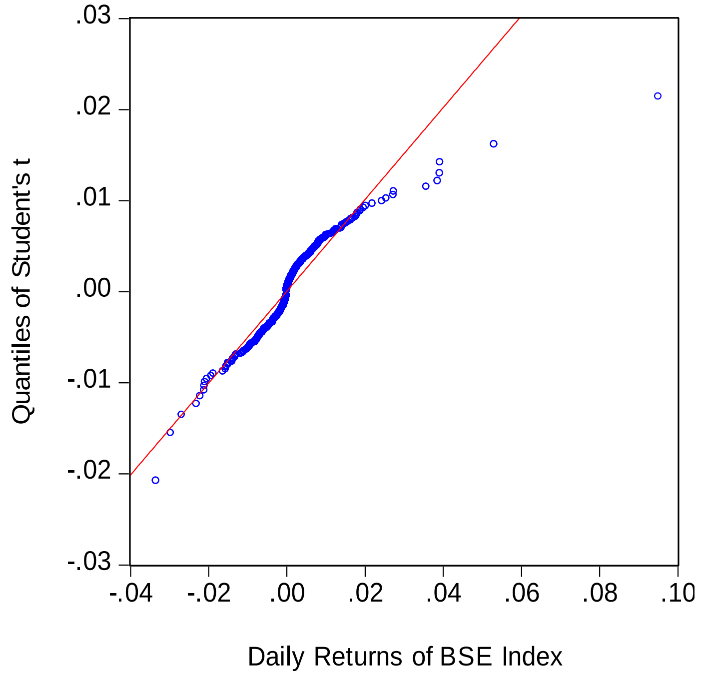
In this study, the quantiles of the empirical distribution function would be compared to the quantiles of the normal and Student-t distributions. As seen in figure 1 & 2 below, the plots suggest that the underlying distribution of the index returns does not fit the normal or Student-t distribution. The plot curves down to the right and up to the left, which implies that the sample data has heavier right tail and fatter left tail respectively relative to the normal distribution. This confirms the earlier indication that the sample data is leptokurtic. To a certain degree, the Student-t distribution fits the underlying distribution of the index returns, however, there is still evidence showing that the distribution of the sample data has heavier tails relative to the Student- t distribution. This finding is in sharp contrast with Bali and Theodossiou (2007a, b) who proposed fitting VaR models based on the assumption of conditional Student t-distribution.

**Figure 1: QQ Plot - Normal**




*The empirical sample is a random sample of 1975 observations compared against the normal distribution.

**Figure 2: QQ Plot - Student t-distribution**




*The empirical sample is a random sample of 1975 observations compared against the student-t distribution.

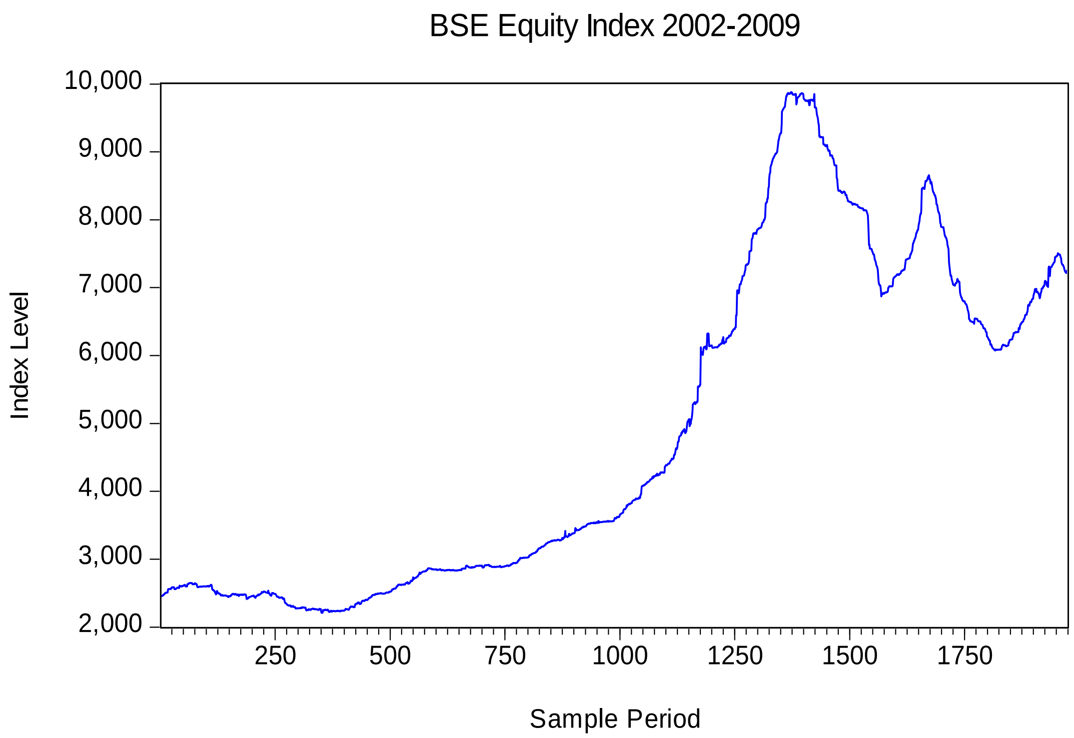
### 3.2. Diagnostic Tests

As noted by Brooks (2008), Dowd (2005) and Campbell et al. (1997) before commencing an analysis on a time series data, the data need not only be checked for stationarity but must also pass a series of diagnostic tests. These tests will in turn provide the necessary information as to the suitability and applicability of a particular methodology. In the next subsections, we provide the necessary diagnostic tests we carried out.

#### *3.2.1. Stationarity Tests*

The trend of the daily index series in figure 3 below shows that the data is non-stationary, and exhibits signs of random walk. Even though the graphical representation shows that the daily index series was non stationary we conducted a more formal stationarity test following from Fuller (1976) and Dickey and Fuller (1979) known in the finance literature as "Augmented Dickey Fuller test (ADF)''. The results as shown in appendix B1 indicate that with a p-value of 0.8425, the null hypothesis that the sample under consideration is non stationary or has a unit root is not rejected.

**Figure 3: BSE Daily Index**



As a remedy, Campbell et al. (1997) and Brooks (2008) argue that first differencing or transforming raw data series into lognormal returns using equation (8) specified below does not only induce stationarity but also ensures convenience in terms of analyzing multi period returns.

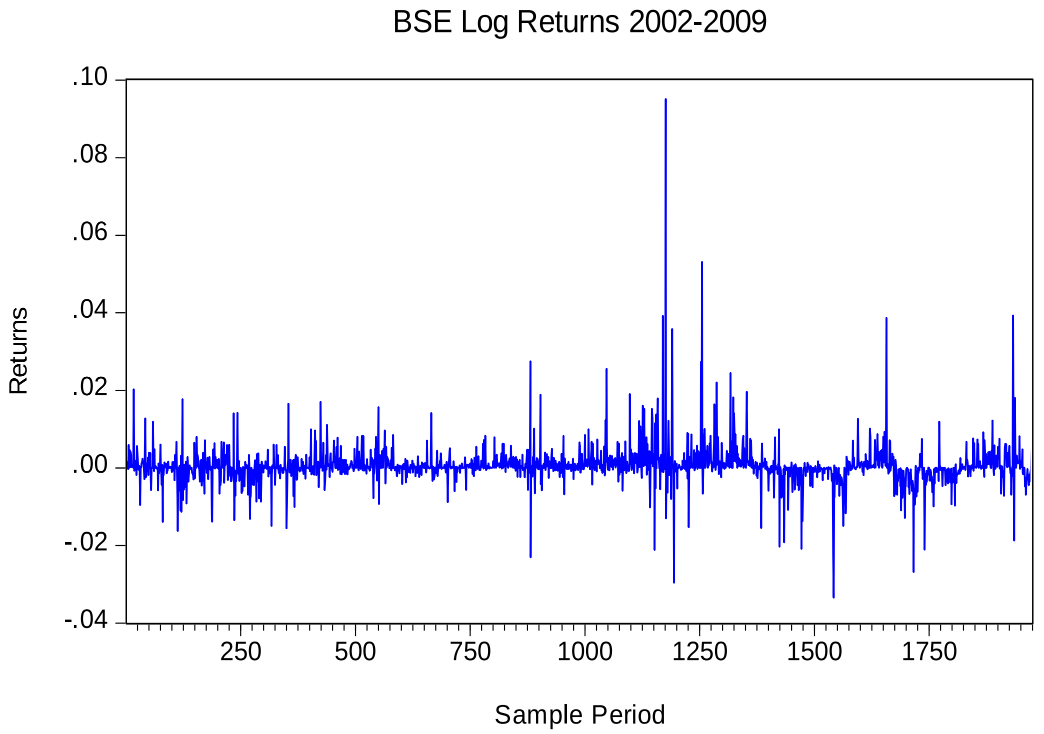
$$Log\ Returns = ln\left(\frac{Index_t}{Index_{t-1}}\right) \qquad \textbf{(8)}$$

Where: $Index_t$ is the index value at time *t*

$Index_{t-1}$ is the index value at time *t-1*

As can be observed from figure 4 below and appendix B2, the lognormal returns are mean reverting and in conformity with the assumption that a stationary series must exhibit properties of a "white noise'' process. More importantly, the ADF test statistic at the conventional significance levels (1% and 5%) also shows that we reject the null assumption of non-stationarity or unit root root test on the lognormal returns.

**Figure 4: BSE Daily Log Returns**



### *3.2.2. Test of Autocorrelation*

A test of autocorrelation is required in the preliminary analysis of a time series data as it provides an insight regarding not only how the analysis should be conducted but also whether time varying volatility parameters need to be considered. We conducted the Ljung Box and Breusch-Godfrey tests on the first five autocorrelation coefficients. The results which can be seen in appendix B3 (a, b, c, d) & B4 (a, b, c, d) for the Breusch-Godfrey and Ljung Box statistic show that the joint null hypothesis that the autocorrelation coefficients are jointly zero cannot be rejected at the 1% significance level for both tests. The Durbin-Watson (DW) test statistic in appendix B3 (a, b, c, d) & B4 (a, b, c, d) is also highly insignificant under the null assumption that there is no autocorrelation in the residuals (see Brooks, 2008). We must point out that the findings are contrary to most studies conducted in emerging markets where conclusive evidence was provided for autocorrelation in the residuals (see Fernandez, 2003; Obil and Sil, 2013; Nartea, Wu and Liu, 2014; Maghyereh and Al-Zoubi, 2006; Lechner and Ovaert, 2010; Harmantizis et al., 2006).

The results do not only suggest that there is no dependency in the returns of the BSE index, which means that today's return does not depend on previous information, but also provides information that time varying volatility models cannot be incorporated into the analysis. From another viewpoint, we can loosely argue that the independence in the returns implies that this small sized rapidly developing market is not of the weak form efficiency (see Campbell et al., 1997; Smith et al., 2002)

### *3.2.3. ARCH Effect Test*

If the goal of the studies is to model VaR based or conditioned on time varying volatility then we first of all need to examine whether the variance is constant (homoscedastic) or is time varying (heteroskedastic). In other words the ARCH effect test attempts to investigate whether there is any correlation in the residuals. We do this by estimating volatility using popular models such as the Exponential Weighted Moving Average (EWMA) or the Generalized Autoregressive Conditional Heteroscedasticity (GARCH).

As per the pre-requisite to incorporating volatility into the analysis as mentioned earlier, we conducted the Engle (1982) test for ARCH effects in Eviews and the results from table 2 below and appendix B5 (a, b, c, d) show that both the F-statistic and Lagrange Multiplier -

statistic are statistically insignificant at both 1% and 5% significance level with p-values of 0.24. This implies that there are no ARCH effects in the BSE Index return series, and as such we cannot model VaR based on conditional or time varying parameters. Following from Brooks (2008) that this test could also be conceived as a test for autocorrelation in the squared residuals, we noted that the results are similar to the Ljung-Box and Breusch Godfrey test we conducted earlier.

**Table 2: Diagnostic Statistics: ARCH Effects in the BSE Index Log Returns**

| Statistic | Entire Sample: 2002-2009 | Sample 1: 2002-2006 | Sample 2: 2003-2007 | Sample 3: 2004-2008 |
|---|---|---|---|---|
| F-Statistic* | 1.350326 | 0.125661 | 0.179547 | 0.796356 |
| Prob(F-Statistic)* | 0.2403 | 0.9866 | 0.9703 | 0.5523 |
| Included observations | 1969 | 1224 | 1225 | 1239 |
| R-squared | 0.003428 | 0.000516 | 0.000736 | 0.003219 |
| Lagrange Multiplier-Statistic* | 6.749054 | 0.631072 | 0.901488 | 3.988277 |
| Prob. Chi-Square* | 0.2400 | 0.9865 | 0.9701 | 0.5511 |

*Null hypothesis as per the description in Brooks (2008) is that the test is one of a joint null hypothesis that all $q$ lags of the squared residuals are not significantly different from zero. The results show that we do not reject the null hypothesis at the conventional significance test levels of 1% and 5% (see probability of F-Statistic and Chi-square)

The sample-by-sample comparison also shows with a p-value in excess of the conventional significance levels (1% and 5%), we do not reject the null assumption that all $q$ lags of the squared residuals are not significantly different from zero. Again the finding here differs significantly from the studies we reviewed in the literature in which ample evidence was provided to suggest that incorporating time varying volatility usually leads to superior VaR estimates (see Obi and Sil, 2013; Onour, 2010; Angelidis, Benos and Degiannakis, 2004)

### 3.3. Methodological Framework

The methodological framework adopted for this study stemmed from the results of the preliminary analysis and diagnostic tests we carried out. We therefore utilized the Extreme Value Theory, which is considered by many in the finance literature as a semi-parametric approach and the Basic Historical Simulation a non parametric approach to estimating VaR for the sample under consideration and also validated the models using a number of backtesting procedures such as the Kupiec (1995) test. Most parametric and semi-parametric approaches to estimating VaR essentially depend on the moments of a distribution which basically implies that various assumptions would have to be made regarding the distributional properties of the data. The non parametric approaches to estimating VaR as the name suggests estimates VaR without making any assumption regarding the underlying properties of asset returns. In the next subsections we provide an in depth discussion on the various parametric and nonparametric approaches we employed in analyzing the data. The next subsection discusses the various approaches we mentioned earlier in the introductory part of this essay and which have been applied in the analysis.

### *3.3.1. Non-parametric method-Basic Historical Simulation Approach*

The Basic Historical Simulation approach, according to Dowd (2005) uses the empirical loss observation to estimating VaR. Dowd (2005) again describes this approach as "a histogram based approach which is conceptually easy to implement, very widely used and has a fairly good historical record". More so, this approach is devoid of the restrictive assumptions made regarding the data at hand, and as such can accommodate the so called "stylized fact'' properties of asset returns and could also be used to estimate VaR for any asset class.

To implement this approach, we used three (3) five (5)-year rolling in-samples of daily actual loss observations organized as follows: 2002-2006, 2003-2007, and 2004-2008. In each in-sample period, there were 1230, 1231 and 1245 actual loss observations, respectively. Using the Microsoft Excel software, we estimated VaR at 99% confidence level for the next trading day by taking sample percentiles over a moving in-sample window. Thus, to obtain an estimate of the next day's VaR at time t in the out of sample period, we used the actual loss observation at time t, and the *n-1* preceding actual losses at the $99^{th}$ percentile for each rolling in-sample period. Next, we validated the model for its appropriateness through the Kupiec (1995) frequency test. In addition, the model was ranked and compared to other model following Lopez's (1998) I frequency-of-tail-losses approach.

### *3.3.2. Semi-Parametric approach-Extreme Value Theory (EVT)*

The Extreme Value Theory (EVT) h models VaR by concentrating on the largest losses in a distribution. In this study, the Peaks over threshold (POT) method was employed. Since POT is used to model losses that are larger than a threshold value as Dowd (2005) suggests, then the threshold value ($u$) for the distribution has to be defined. Suppose that L is a stochastic loss variable with an unknown cummulative density function, F. We could think of this L as the loss beyond the predetermined threshold value which could either be in the right or left tail of the distribution depending on the skewness of the distribution. This implies that: $\Pr(L < l) = F(\ell)$ which can also be written as $\Pr(L \leq VaR) = \alpha = F(VaR)$.

Revisiting the equation above, we can rewrite the relationship as shown below where the interest is to solve the equation for $\alpha = F(VaR)$. From the preceding discussion, we assume that the stochastic loss (L) is to the right with two scenarios presented below:

$A: L \leq \ell + u$

$B: L > u$

We can express the conditional probability between the above relationships as follows:

$$F_u(\ell) = \Pr(A|B) = \frac{\Pr\,(A \cap B)}{\Pr\,(B)} = \frac{F(\ell + u) - F(u)}{1 - F(u)}$$

$$F_u(\ell - u) = \frac{F(\ell) - F(u)}{1 - F(u)} \qquad \textbf{(9)}$$

In order to solve for $\alpha = F(VaR)$, we need to make a couple of assumptions regarding the parameters in the equation above, and for simplicity we assume the following:

$F(VaR) = \alpha = F(\ell)$

$F_u = 1 - \frac{N_u}{N}$ , where $N$ = total observations; $N_u$= observations exceeding the threshold value

$F_u(\ell - u) = G(\ell - u)$, from the Pickand Balkema-deHaan theorem, where G represents the cumulative Generalized Pareto Distribution (GPD) and is shown below:

$$G(\ell - u) = \begin{cases} 1 - \left(1 + \xi \dfrac{\ell - u}{\beta}\right)^{-\frac{1}{\xi}} \\ 1 - exp\left(-\dfrac{\ell - u}{\beta}\right) \end{cases} for\ \xi \neq 0, and\ \xi = 0$$

The parameters xsi ($\xi$) and beta ($\beta$) which is estimated via the maximum log likelihood approach are considered as shape and scale parameters and they measure the fatness or heaviness of the tails of a distribution and loosely risk respectively. If we substitute the parameters into the equation (9) above, we come up with two equations for VaR based on the definition of the GPD equation above. We then estimated the unconditional VaR underpinned by EVT following equations (10 & 11) specified below.

$$VaR = u + \frac{\beta}{\xi}\left[\frac{N}{N_u}(1-\alpha)^{-\xi} - 1\right] \; for\; \xi > 0 \tag{10}$$

$$VaR = u - \beta ln\left[\frac{N}{N_u}(1-\alpha)\right] \; for\; \xi = 0 \tag{11}$$

### *3.3.3. Estimation of GPD Parameters*

The modeling of VaR underpinned by EVT requires that we estimate some of the parameters which are defined in equation (10 & 11). We followed the maximum log likelihood equation specified in equation (12 & 13) below to maximize the values of beta and xsi in Microsoft Excel bearing in mind that unlike the block maxima approach underpinned by the Generalized Extreme Value (GEV) in which the latter could take on negative values, the same assumption does hold for the Peaks over Threshold (POT) underpinned by the Generalized Pareto Distribution (GPD). In effect the scale (beta) and shape (xsi) parameters must both take on positive values since Dowd (2005) argues that positivity of the latter parameter could “correspond to the data being heavy tailed.’’ Furthermore, Dowd (2005) argues that there is no developed approach to determining the appropriate threshold value. Since there is no defined approach, we therefore set the threshold values for the sample periods based on a simple premise that the losses should not exceed 5% of the total losses in each sample.

$$logL(\beta,\xi) = -mln\beta - \left(1+\frac{1}{\xi}\right)\sum_{i=1}^{m} ln\left(1+\xi\frac{l_u^i - u}{\beta}\right) \; for\; \xi > 0 \tag{12}$$

$$logL(\beta) = -mln\beta - \frac{1}{\beta}\sum_{i=1}^{m} ln\left(l_u^i - u\right) \; for\; \xi = 0 \tag{13}$$

Where: $m$ denotes the number of observations beyond the threshold value ($u$)
$l_u^i$ denotes the sorted actual losses beyond the threshold value ($u$)

### *3.3.4. Model Validation Approaches*

The VaR models were validated using the Kupiec (1995) frequency test while Lopez (1998) I frequecncy-of-tail-losses were used to rank them. In applying the Kupiec (1995) frequency test at the 99% confidence level, the number of exceedances and non-violations were denoted by ones and zeros respectively. This means that under this test we would expect the sample in each test period (pre, crisis and post crisis) to consist of zeros and ones which represent violations and non-violations. We defined the expected or predicted frequency of violation following from Dowd (2005) as shown below:

$$Expected\ VaR\ Violations(m) = (1 - \alpha) * N$$

The expected number of VaR violations is compared with the actual number of violations which we shall denote as $X$. We then calculate the probability of either observing $X \geq m$ or $X \leq m$ violations under the assumption that the underlying model is correct. The decision rule which represents the final aspect in applying the Kupiec test exacts that if the estimated probability exceeds the statistical significance level of interest then the underlying VaR model should not be rejected. If the two sided Kupiec test is implemented via the confidence interval approach, then the underlying model is rejected if the actual number of violations falls outside the lower and upper boundaries (Kupiec, 1995).

Even though we can statistically conduct this test as we described in the preceding section to obtain a confidence interval or the probability value in order to make a decision regarding whether the underlying model should be rejected or not, a visual comparison of the actual with the expected violations could provide us with a fair picture of whether the underlying model would yield consistent results.

In ranking the models we employed Lopez's (1998) I test which is described as a Quadratic Probability Score (QPS) function to compare and rank the models used to estimate VaR for each test period. The QPS, which is specified in the subsequent equation, takes on a value between zero (0) and two (2), and the closer this value to zero (0), the better the model.

$$QPS = \frac{2}{n}\sum_{t=1}^{n}(c_t - p)^2 \tag{14}$$

Where: $n$ = total observations for the test period

$p$ = significance level of the test

$c_t$ = a binary loss function represented by the equation below

$$C_t = \begin{cases} 1 & if \quad L_t > VaR_t \\ 0 & \quad\;\; L_t \leq VaR_t \end{cases}$$

# 4. Empirical Data Analysis and Results

In this section we discuss the estimation methods and also present the empirical results of the study discussing the findings vis-à-vis existing literature.

### *4.1. Estimation of tail parameters (EVT)*

As pointed out earlier in the methodology section following from the arguments put forward by Dowd (2005), there is no developed approach to determining the appropriate threshold value. The process of choosing this value therefore results in a trade off as many or few observations could be considered. We therefore set the threshold values for the sample periods based on a simple premise that the losses should not exceed 5% of the total losses in each sample. We basically inverted the lognormal returns into negatives to give us the losses and also to represent the direction of the third moment of the distribution. As can be seen from the table (3) below, the following exceedances which are less than the 5% we mentioned earlier were observed when we set the threshold at 0.65% for all the sample periods.

**Table 3: Unconditional EVT Parameters (in percentages)**

| | $\xi = 0$ | $\xi > 0$ | | No. of observations & threshold | | | |
|---|---|---|---|---|---|---|---|
| | β (beta) | β (Beta) | ξ (xsi) | N | u | Nu | N/Nu |
| Sample 1 | 0.457408 | 0.410101718 | 0.10526214 | 1230 | 0.65 | 39 | 31.53846154 |
| Sample 2 | 0.530242 | 0.442642322 | 0.174532744 | 1231 | 0.65 | 35 | 35.17142857 |
| | | | | | | | |
| Sample 3 | 0.597195 | 0.405036837 | 0.363757515 | 1245 | 0.65 | 42 | 29.64285714 |

***Beta(**β), xsi(ξ) represent the scale and shape parameter respectively and were estimated using equation (12 & 13) in section 3. Parameters u, Nu and N represent the arbitrarily selected threshold value, the number of losses beyond the threshold value and the total observations in each sample, respectively.

As can be observed from table (3) above the value of the xsi which is considered as a measure of the shape or tail of the underlying distribution shows that the distribution was more positively skewed in sample 3 (xsi= 0.363) than the other sample periods under consideration. The results are not only consistent with the earlier findings, we discussed under descriptive statistics, but also with the literature that the distribution is heavy tailed if the value of the shape parameter exceeds zero (Dowd, 2005). The scale parameter, which is measured by the beta, shows a value of 0.5972 for sample 3 is higher than the other sample periods. Loosely interpreting the beta as a measure of market risk shows that on the average the risk of this market is lower than the standard beta measure of market risk. This finding suggests that investors who are risk averse can consider diversifying their investment portfolios in this market since the risk is minimal compared to other emerging markets in Sub-Saharan Africa.

### *4.2. VaR estimation*

We estimated VaR following the two main approaches from the analysis of the preliminary statistics, which indicate that fitting the VaR model underpinned by the normal and Student-t distribution (see the JB and QQ test) assumptions could lead to distortions in estimating the risk measure. We therefore focused on the Basic Historical Simulation and the unconditional POT following from the diagnostic tests discussed earlier. We computed VaR at the 99% confidence interval for a one day holding period for the selected test periods (pre-crisis, crisis, and post crisis) also following from the argument advanced earlier that a short horizon and a higher confidence interval are chosen if the purpose is to backtest a model. We estimated unconditional VaR underpinned by the GPD following from equation 10 & 11 (for $\xi > 0$ and $\xi \neq 0$ respectively) while the Basic Historical Simulation was estimated using the percentile function in Excel.

The results which can be seen in table (4) below indicates that VaR estimated using the unconditional POT for all the periods seem to be higher when xsi is set to zero. We can also observe that the VaR estimates using the Basic Historical Simulation approach seem to yield superior results compared to the unconditional EVT. The caveat with this standard approach to estimating VaR as was pointed out by Fernandez (2003) is that it is likely to yield superior results when the number of observations is extremely large relative to a few sample length.

**Table 4: VaR estimates in percentage at the 99% confidence interval**

| | Unconditional EVT VaR* | | Basic Historical Simulation VaR* |
|---|---|---|---|
| | ξ = 0 | ξ > 0 | |
| Pre crisis | 1.177831791 | 1.15318393 | 0.925392-1.251667 |
| | | | |
| Crisis | 1.204069139 | 1.157395648 | 1.062775-1.350105 |
| | | | |
| Post crisis | 1.376158361 | 1.269428024 | 1.340206-1.511574 |

*VaR was estimated for the periods 2007, 2008 and 2009 and represent pre crisis, crisis, and post crisis as per the definition in the essay. Unconditional EVT is constant for the out-of-sample test periods while the Basic Historical Simulation VaR provides a lower and an upper boundary or values of VaR for the periods represented in the table.

More so the results from above indicate that the estimate of VaR using either the unconditional EVT or Basic Historical Simulation approach was higher during the post crisis period than the other two sub sample periods. Even though there is no empirical proof to support the argument, we could speculate that the global financial crisis which occurred in 2008 actually had an impact on emerging markets since VaR for the post crisis test period was estimated using the in-sample losses which comprised indices from 2004-2008. A look at both approaches to estimating VaR also shows that the Basic Historical approach recorded the highest estimate during the post crisis test period compared to the other test periods. The rationale behind this, as argued by Dowd (2005) and seen as a potential weakness of the non-parametric approach is that during periods of low or high volatility (normal or extreme events), the Basic Historical approach could either underestimate or overestimate risk respectively.

The VaR results in table 4 above further shows that in periods of tranquility (pre and post crisis periods) and crisis periods the Basic Historical Simulation yielded superior estimates. For instance, before the global financial crisis, the minimum and maximum estimates of VaR from Basic Historical Simulation model were approximately 0.92% and 1.25%, respectively. In contrast, the unconditional EVT VaR estimate was approximately 1.18%, which is higher than the Basic Historical Simulation. These findings are contrary to the empirical evidence of Bao, Lee and Saltoglu's (2004) study on five Asian markets that riskmetrics models performed best during periods of low volatility while EVT based approaches provided superior estimates during crisis periods.

### *4.3. Backtesting and Comparison of VaR models*

We conducted the Kupiec (1995) frequency test as was described in the preceding section, and the results which can be seen in table (5) below show that both the unconditional EVT and Basic Historical approaches pass the test at the 1% significance level. Again the study shows that the number of exceedances under the EVT approach was less than the Basic Historical Simulation which is not underpinned by any distributional assumption. As can be seen from table 5 below the post crisis period recorded the least number of violations compared to the other test periods indicating that the estimates of VaR, which factored in extreme losses exceeded the observed losses in out-of-sample test period. This again points to the argument we have advanced in this discourse that measures of risk seem to perform better whenever extreme losses which result from high impact and low probability events are considered.

**Table 5: Model validation via Kupiec frequency test at the 99% Confidence Level**

| | Unconditional EVT | | Basic Historical Simulation | Expected exceedances | Kupiec test | | |
|---|---|---|---|---|---|---|---|
| | Actual Number of Violations/Exceedances | | | EVT & BHS | Unconditional EVT | | BHS |
| Crisis | $\xi = 0$ | $\xi > 0$ | | | $\xi = 0$ | $\xi > 0$ | |
| Pre | 5 | 5 | 6 | 3 | 0-6 **(0.1052)*** | 0-6 **(0.1052)*** | 0-6 **(0.0399)*** |
| | | | | | | | |
| Crisis | 5 | 6 | 5 | 3 | 0-6 **(0.1065)*** | 0-6 **(0.0405)*** | 0-6 **(0.1065)*** |
| | | | | | | | |
| Post | 2 | 2 | 2 | 3 | 0-6 **(0.5561)*** | 0-6 **(0.5561)*** | 0-6 **(0.5561)*** |

*Numbers in parenthesis indicate the probability values of the test at the conventional 1% significance level while 0-6 represent the lower and upper boundaries respectively of the two sided Kupiec test. The results show that we do not reject the underlying models (Unconditional EVT and BHS) during the sample periods described since the actual violations fall within the upper and lower boundaries of the Kupiec test. This argument holds for the probability values at the conventional significance level of 1%

Even though there is empirical evidence that the Basic Historical Simulation could perform better, care needs to taken as this approach seems to work best when there is a large number of observations (see Fernandez, 2003). This study is similar to Maghyereh and Al-Zoubi's

(2006) findings, which failed to provide any conclusive evidence regarding whether the historical simulation or POT should be considered in Middle East & North African (MENA) markets. The findings in this study are significantly different from Angelidis and Benos (2005), Burchi (2013), Sinhua and Chamu (2005) who proposed historical simulation.

Onour's (2010) study in some Gulf Cooperation Council Countries as well as Gilli and Kellezi's (2006) study also seemed to suggest that the POT underpinned by the Generalized Pareto Distribution seemed to perform better over other approaches which differ from the findings of this study. The study of Seymur and Polakow (2003) in South Africa even though compared the EVT method with the Basic Historical and Volatility Weighted Historical Simulation (VWHS) approaches, the empirical findings which revealed that modeling VaR based on the VWHS technique yielded superior results is somewhat different from the findings in this study.

According to the Basel Committee's three zones backtesting approach (Basel Committee on Banking Supervision, 1996, 2004), a model is considered to be in the green zone if the number of violations falls between zero and four (0-4), in the yellow region if the exceedances lie between five and nine (5-9) and in the red area if the exceptions go beyond ten (10). The interpretation provided here is that any model with exceptions in the green, yellow or red regions are considered to be accurate, semi-accurate and inaccurate respectively. Extending this argument to the analysis shows that the violations for both the unconditional POT and the Basic Historical Simulation during the pre crisis and crisis test periods fall within the yellow zone while both approaches fall in the green zone in the post crisis period. The point we are trying to highlight is that the models developed in this study can be accepted by regulatory agencies.

In comparing and ranking the two models which both passed the Kupiec (1995) frequency test, we relied on the frequency of tail loss method, popularly known as Lopez (1998) I approach as specified in equation (14). The results which can be observed in table (6) shows that in all the test periods VaR was estimated and compared with the out-of-sample loss observations, the Unconditional EVT performed better compared to the Basic Historical Simulation during the pre-crisis test period. The other test periods yielded the same QPS value since they resulted in the same number of actual VaR violations. The findings that the EVT performs better than Basic Historical Simulation when the Lopez (1998) *I* frequency-of-tail loss is used to rank the models is consistent with previous empirical findings (see Gilli and Kellezi, 2006; Uppal and Mangla, 2013; Nartea et al., 2014; Harmantzis et al., 2006; Kourouma, Dupre, Sanfilippo and Taramasco, 2012; Silva and Mendes, 2003). It is also interesting to note that this finding is significantly different from the empirical evidence provided by Burchi (2013) and Angelidis and Benos (2005) who seemed to suggest that the Basic Historical Simulation approach to estimating VaR yields superior estimates. We therefore suggest that since the POT underpinned by unconditional EVT seemed to be ranked higher than the Basic Historical Simulation, policy makers in this market should rely on VaR estimates based on EVT.

**Table 6: Comparing and Ranking the models using Lopez (1998) I approach**

| | Unconditional EVT | | | | Basic Historical Simulation | | Comparison |
|---|---|---|---|---|---|---|---|
| Period | Actual Violations (xsi=0) | QPS* | Actual Violations (xsi>0) | QPS* | Actual Violations | QPS* | Comments |
| Pre crisis | 5 | 0.03971 | 5 | 0.03972 | 6 | 0.04762 | **EVT performs better** |
| Crisis | 5 | 0.03956 | 6 | 0.04743 | 5 | 0.03956 | **Inconclusive** |
| Post crisis | 2 | 0.01620 | 2 | 0.01620 | 2 | 0.01620 | **Inconclusive** |

*The Quadratic Probability Score (QPS) test aims to rank the two models which both passed the Kupiec (1995) frequency based test. The rule here is that the QPS must take on a value between zero (0) and two (2), and the closer this value is to zero the better. We ranked the two models and provided a general comment on which of them performed better than during each test period.

## 5. Summary, Conclusions and Recommendations

This section provides a summary of the study, conclusions of the empirical results and proffers recommendation for further research.

In every market, investors are basically concerned with the amount of cash flows they can get on their investment. After most emerging markets experienced the trickle down effect of the collapse of the financial market in the United States and other developed markets in 2008, most investors who had previously been unconcerned about issues related to risk management begun seeking answers to questions like how much, when, what is the probability that this amount of money could be lost in the future. The answer to these questions as we mentioned in the introductory section is summed up in the risk measurement tool referred to as VaR, a risk measure which provides most of the information required by market actors to make prudent decisions.

The approach to estimating VaR varies considerably depending on innumerable factors key of which is the underlying data and assumptions made regarding it. This study attempted to model VaR for a small sized developing market in Sub-Saharan Africa, which Ikoku and Hosseini (2008) pointed out provides the best inflation adjusted return and also has the highest number of foreign investors and which has also received limited interest from policy analysts and scholars alike. The preliminary analysis conducted showed that the standard deviation of this market was lower than what was found in most studies carried out in emerging contexts; and the tails of the distribution were not only fatter than the developed economies, but also ‘’bigger’’ than the markets classified as “medium and large” in the emerging economy brackets. The quantile-by-quantile (QQ) plot even showed that the distribution has fatter tails relative to the Student-t distribution. In effect the tails of the distribution exhibited the so called “stylized fact’’ property of financial asset returns, as is evidenced in the studies of Susmel (2001) and Fernandez (2003). This finding implies that estimating VaR under assumptions of normality or the Student t-distribution could lead to underestimation of risk which policy makers need to make informed decisions.

In order to incorporate volatility into any analysis, a stationary data series must show that there is indeed some sort of dependency in the residuals because current estimates of volatility are based on previous information which is reflected in the residuals. What this essentially means is if formal tests as we conducted under the diagnostics show that there is no such relationship in the residuals then volatility measures cannot be incorporated into the estimate of VaR. However, the findings suggested that such dependency in the residuals does not exist giving credence to the fact that modeling VaR based on time varying volatility assumptions could lead to distortions and thence affect risk management strategies policy makers intend to implement.

As we pointed out earlier the independence in the residuals can also be loosely conceived to mean that this market is of the weak form efficiency, thus serving as a red flag to signal arbitrageurs who may want to make riskless profits from trade using previous information. From the foregoing discussions, we estimated VaR using the Basic Historical Simulation which does not have any restrictive distributional assumptions and the Peaks over Threshold (POT) based on the Generalized Pareto Distribution. The results from the EVT parameters (beta) reveal that the market risk in this small sized developing market is lower than in most economies within the emerging market context thus offering an opportunity for diversification of risk.

More importantly, even though the two models passed the Kupiec test for the pre-crisis, crisis and post crisis test periods, and the Basic Historical Simulation yielded superior VaR estimates compared to the unconditional POT, caution need to be taken when using the former as it could perform better when the sample of observations is extremely large as we had in the analysis. We therefore suggest that as an alternative, policy makers need to look at the number of violations possibly in each approach in deciding which to implement in their decision making framework or rank the models using Lopez's (1998) I frequency-of-tail-losses approach. We also recommend that policy makers should make good use of all the backtesting and comparison approaches to choosing and ranking methods which may pass the Kupiec (1995) frequency and the Christopherssen (1998) test.

Again the comparative analysis of the three sub sample periods shows that the various measures we analyzed seemed to perform better or worse during the post crisis test period in 2009 which were estimated using in-sample loss observations between the years 2004-2008. Considering the established fact that the global financial crisis, which is believed to be an extreme event occurred during that in-sample period, we recommend that policy makers in small sized emerging markets should consider modeling risk measures underpinned by the Extreme Value Theory since it has the ability to factor in such events which the other approaches do not consider.

We conclude this study by pointing out that policy makers in every market need to understand the dynamics within the market in which they operate when they are confronted with decisions regarding which approach to employ to estimate VaR. As we noted in the literature review a number of studies have suggested countless approaches which are likely to perform in the markets in which the studies were conducted, but not applicable in other contexts. The onus therefore lies on market actors to understand the distributional property of the data they are analyzing in order to determine which approach will capture Value-at-Risk (VaR). Since this study modeled VaR using equity indices from a single market, future research can investigate how the several approaches may fare in more than one market using bank trading books (Profit/Loss) data instead of an equity index.

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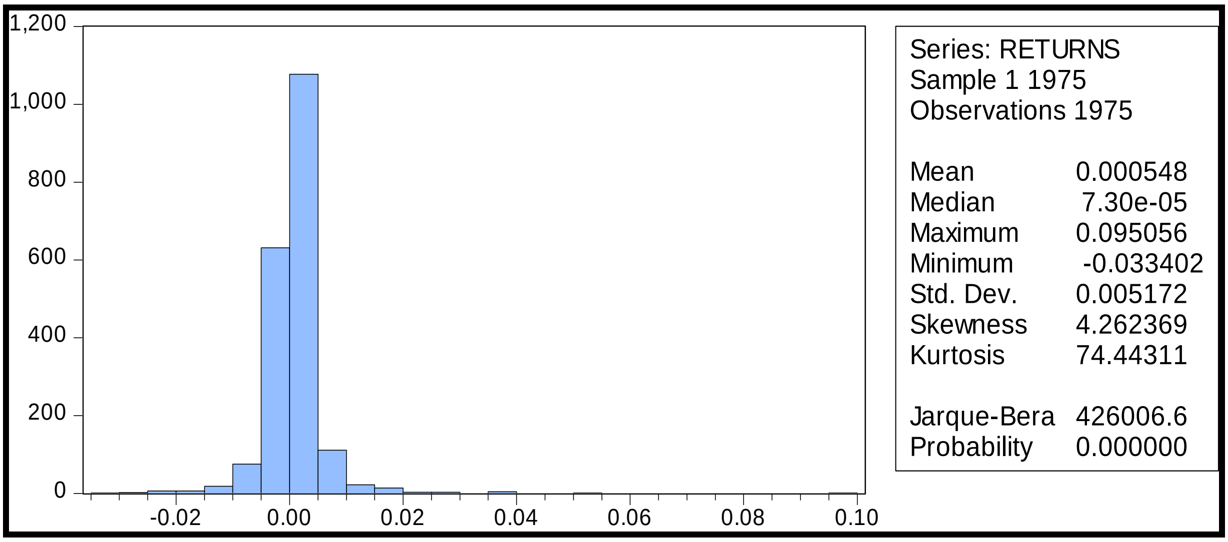
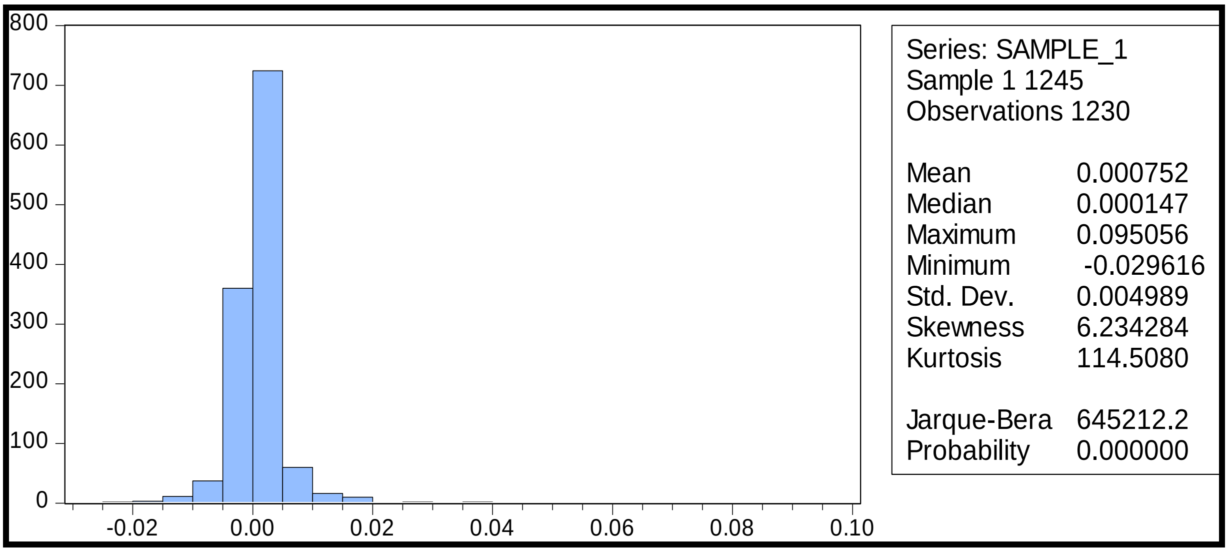
# APPENDIX A:

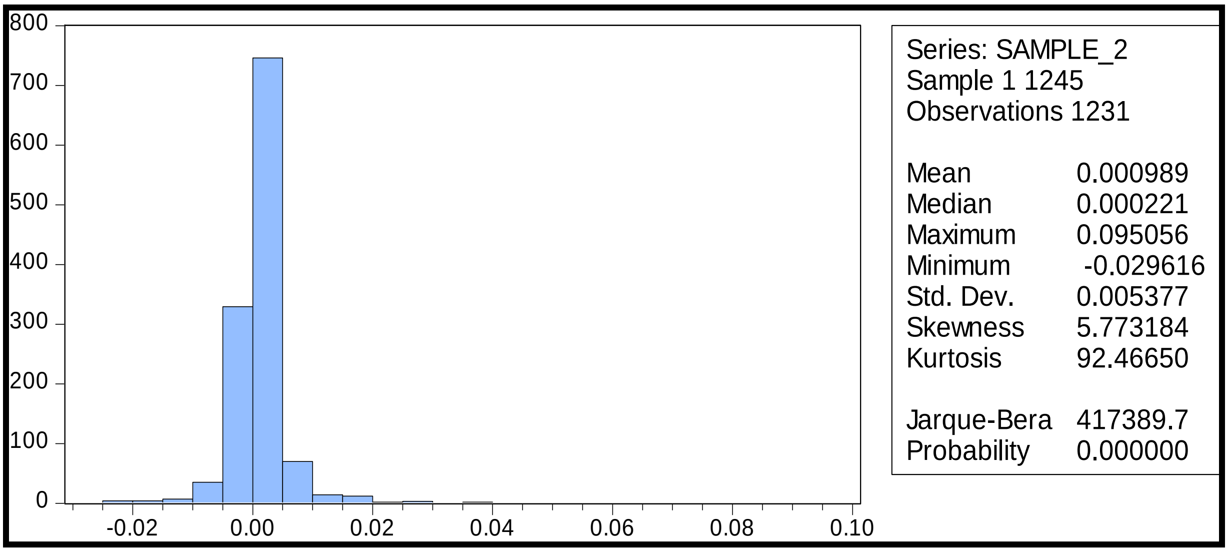
## Appendix A1: Summary Statistics Entire Sample: 2002-2009



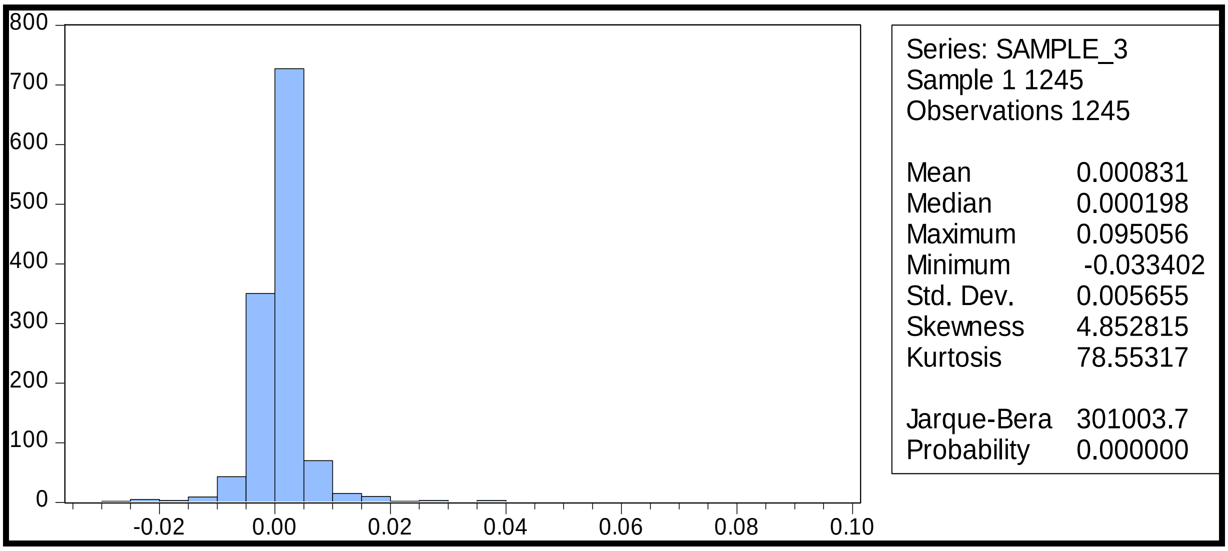

## Appendix A2: Summary Statistics Sample 1: 2002-2006



**Appendix A3: Summary Statistics Sample 2: 2003-2007**




**Appendix A4: Summary Statistics Sample 3: 2004-2008**



## Appendix B1: Test for Stationarity - BSE Index

Null Hypothesis: INDEX has a unit root
Exogenous: Constant
Lag Length: 9 (Automatic - based on SIC, maxlag=25)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -0.709124 | 0.8425 |
| Test critical values: | 1% level | -3.433478 | |
| | 5% level | -2.862808 | |
| | 10% level | -2.567492 | |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(INDEX)
Method: Least Squares
Date: 05/05/14 Time: 12:32
Sample (adjusted): 11 1975
Included observations: 1965 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| INDEX(-1) | -0.000199 | 0.000281 | -0.709124 | 0.4783 |
| D(INDEX(-1)) | 0.052176 | 0.022575 | 2.311268 | 0.0209 |
| D(INDEX(-2)) | 0.064888 | 0.022522 | 2.881114 | 0.0040 |
| D(INDEX(-3)) | 0.060009 | 0.022542 | 2.662085 | 0.0078 |
| D(INDEX(-4)) | 0.035021 | 0.022327 | 1.568566 | 0.1169 |
| D(INDEX(-5)) | 0.044446 | 0.022318 | 1.991481 | 0.0466 |
| D(INDEX(-6)) | 0.149347 | 0.022326 | 6.689250 | 0.0000 |
| D(INDEX(-7)) | 0.060546 | 0.022543 | 2.685766 | 0.0073 |
| D(INDEX(-8)) | 0.086182 | 0.022539 | 3.823769 | 0.0001 |
| D(INDEX(-9)) | 0.063017 | 0.022600 | 2.788289 | 0.0054 |
| C | 1.885009 | 1.528068 | 1.233590 | 0.2175 |

| | | | |
|---|---|---|---|
| R-squared | 0.096001 | Mean dependent var | 2.415165 |
| Adjusted R-squared | 0.091375 | S.D. dependent var | 31.73959 |
| S.E. of regression | 30.25475 | Akaike info criterion | 9.662766 |
| Sum squared resid | 1788594. | Schwarz criterion | 9.694021 |
| Log likelihood | -9482.667 | Hannan-Quinn criter. | 9.674252 |
| F-statistic | 20.75079 | Durbin-Watson stat | 2.003523 |
| Prob(F-statistic) | 0.000000 | | |

*Augmented Dickey-Fuller test shows that, at a *p-value* of 0.8425, the null hypothesis that BSE Index has a unit root could not be rejected at 1%,5% and 10% significance level, respectively. This indicates that the data is non stationary.

## Appendix B2: Test for Stationarity - BSE Log returns

Null Hypothesis: LOGRETURNS has a unit root
Exogenous: Constant
Lag Length: 7 (Automatic - based on SIC, maxlag=25)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -10.37244 | 0.0000 |
| Test critical values: | 1% level | -3.433475 | |
| | 5% level | -2.862807 | |
| | 10% level | -2.567491 | |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LOGRETURNS)
Method: Least Squares
Date: 05/05/14 Time: 12:33
Sample (adjusted): 9 1975
Included observations: 1967 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LOGRETURNS(-1) | -0.501413 | 0.048341 | -10.37244 | 0.0000 |
| D(LOGRETURNS(-1)) | -0.467345 | 0.047815 | -9.774129 | 0.0000 |
| D(LOGRETURNS(-2)) | -0.398853 | 0.046740 | -8.533454 | 0.0000 |
| D(LOGRETURNS(-3)) | -0.345997 | 0.044118 | -7.842625 | 0.0000 |
| D(LOGRETURNS(-4)) | -0.325915 | 0.040728 | -8.002315 | 0.0000 |
| D(LOGRETURNS(-5)) | -0.290478 | 0.036695 | -7.915946 | 0.0000 |
| D(LOGRETURNS(-6)) | -0.144810 | 0.031240 | -4.635437 | 0.0000 |
| D(LOGRETURNS(-7)) | -0.088437 | 0.022513 | -3.928292 | 0.0001 |
| C | 0.000270 | 0.000116 | 2.318727 | 0.0205 |

| | | | |
|---|---|---|---|
| R-squared | 0.492308 | Mean dependent var | -2.79E-06 |
| Adjusted R-squared | 0.490234 | S.D. dependent var | 0.007043 |
| S.E. of regression | 0.005029 | Akaike info criterion | -7.742689 |
| Sum squared resid | 0.049516 | Schwarz criterion | -7.717139 |
| Log likelihood | 7623.935 | Hannan-Quinn criter. | -7.733300 |
| F-statistic | 237.3338 | Durbin-Watson stat | 2.009012 |
| Prob(F-statistic) | 0.000000 | | |

*By transforming the data into log returns, Augmented Dickey-Fuller test shows that with a highly significant *p-value* of 0.0000, the null hypothesis that BSE log returns has a unit root is rejected at 1%,5% and 10% significance level, respectively. This indicates that the data is stationary.

## Appendix B3a: Test for Autocorrelation: Breusch-Godfrey Serial Correlation LM Test

Entire Sample: 2002-2009

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No autocorrelation in the residuals

| | | | |
|---|---|---|---|
| F-statistic | 2.978695 | Prob. F(5,1966) | 0.0110 |
| Obs*R-squared | 14.84143 | Prob. Chi-Square(5) | 0.0111 |

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 05/05/14 Time: 12:39
Sample: 2 1975
Included observations: 1974
Presample missing value lagged residuals set to zero.

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 1.49E-05 | 0.000439 | 0.034049 | 0.9728 |
| AR(1) | -0.009510 | 0.007317 | -1.299715 | 0.1939 |
| MA(1) | 0.043054 | 0.018220 | 2.362959 | 0.0182 |
| RESID(-1) | -0.072300 | 0.026527 | -2.725501 | 0.0065 |
| RESID(-2) | -0.028587 | 0.025791 | -1.108414 | 0.2678 |
| RESID(-3) | -0.045084 | 0.025280 | -1.783376 | 0.0747 |
| RESID(-4) | -0.071793 | 0.024910 | -2.882084 | 0.0040 |
| RESID(-5) | -0.054601 | 0.024465 | -2.231806 | 0.0257 |

| | | | |
|---|---|---|---|
| R-squared | 0.007518 | Mean dependent var | 1.66E-06 |
| Adjusted R-squared | 0.003985 | S.D. dependent var | 0.005005 |
| S.E. of regression | 0.004995 | Akaike info criterion | -7.756522 |
| Sum squared resid | 0.049061 | Schwarz criterion | -7.733876 |
| Log likelihood | 7663.687 | Hannan-Quinn criter. | -7.748201 |
| F-statistic | 2.127608 | Durbin-Watson stat | 1.993186 |
| Prob(F-statistic) | 0.037891 | | |

*Breusch-Godfrey autocorrrelation test the null hypothesis that there is no autocorrelation in the residuals. As the results shows, the *p-value* is insignificant at 1% significance level, hence the null hypothesis cannot be rejected, indicating that there is no autoorrelation in the residuals of the entire sample size.

**Appendix B3b: Test for Autocorrelation: Breusch-Godfrey Serial Correlation LM Test**

Sample 1: 2002-2006

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No autocorrelation in the residuals

| | | | |
|---|---|---|---|
| F-statistic | 0.306280 | Prob. F(2,1224) | 0.7362 |
| Obs*R-squared | 0.614753 | Prob. Chi-Square(2) | 0.7354 |

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 05/02/14 Time: 17:02
Sample: 2 1230
Included observations: 1229
Presample missing value lagged residuals set to zero.

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -6.27E-08 | 0.000140 | -0.000449 | 0.9996 |
| AR(1) | -0.098928 | 0.209399 | -0.472437 | 0.6367 |
| MA(1) | 0.126963 | 0.246499 | 0.515064 | 0.6066 |
| RESID(-1) | -0.031024 | 0.052623 | -0.589550 | 0.5556 |
| RESID(-2) | 0.031973 | 0.041710 | 0.766537 | 0.4435 |

| | | | |
|---|---|---|---|
| R-squared | 0.000500 | Mean dependent var | -1.18E-07 |
| Adjusted R-squared | -0.002766 | S.D. dependent var | 0.004981 |
| S.E. of regression | 0.004988 | Akaike info criterion | -7.759352 |
| Sum squared resid | 0.030458 | Schwarz criterion | -7.738547 |
| Log likelihood | 4773.122 | Hannan-Quinn criter. | -7.751524 |
| F-statistic | 0.153140 | Durbin-Watson stat | 2.001433 |
| Prob(F-statistic) | 0.961619 | | |

*Breusch-Godfrey autocorrrelation test the null hypothesis that there is no autocorrelation in the residuals. As the results shows, the *p-value* is highly insignificant at both 1% and 5% significance level respectively, hence the null hypothesis cannot be rejected, indicating that there is no autoorrelation in the residuals of the first sub sample.

**Appendix B3c: Test for Autocorrelation: Breusch-Godfrey Serial Correlation LM Test**

Sample 2: 2003-2007

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No autocorrelation in the residuals

| | | | |
|---|---|---|---|
| F-statistic | 3.851455 | Prob. F(2,1225) | 0.0215 |
| Obs*R-squared | 7.686019 | Prob. Chi-Square(2) | 0.0214 |

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 05/02/14 Time: 17:07
Sample: 2 1231
Included observations: 1230
Presample missing value lagged residuals set to zero.

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -5.74E-07 | 0.000150 | -0.003827 | 0.9969 |
| AR(1) | -0.085780 | 0.194130 | -0.441871 | 0.6587 |
| MA(1) | 0.120356 | 0.228768 | 0.526105 | 0.5989 |
| RESID(-1) | -0.006444 | 0.051593 | -0.124905 | 0.9006 |
| RESID(-2) | 0.093306 | 0.040810 | 2.286337 | 0.0224 |

| | | | |
|---|---|---|---|
| R-squared | 0.006249 | Mean dependent var | 1.05E-07 |
| Adjusted R-squared | 0.003004 | S.D. dependent var | 0.005369 |
| S.E. of regression | 0.005361 | Akaike info criterion | -7.615271 |
| Sum squared resid | 0.035207 | Schwarz criterion | -7.594480 |
| Log likelihood | 4688.392 | Hannan-Quinn criter. | -7.607449 |
| F-statistic | 1.925727 | Durbin-Watson stat | 2.005790 |
| Prob(F-statistic) | 0.103821 | | |

*Breusch-Godfrey autocorrrelation test the null hypothesis that there is no autocorrelation in the residuals. As the results shows, the *p-value* is insignificant at 1% significance level, hence the null hypothesis cannot be rejected, indicating that there is no autoorrelation in the residuals of the second sub sample.

## Appendix B3d: Test for Autocorrelation: Breusch-Godfrey Serial Correlation LM Test

Sample 3: 2004-2008

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No autocorrelation in the residuals

| | | | |
|---|---|---|---|
| F-statistic | 2.864866 | Prob. F(2,1239) | 0.0574 |
| Obs*R-squared | 5.725807 | Prob. Chi-Square(2) | 0.0571 |

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 05/02/14 Time: 17:15
Sample: 2 1245
Included observations: 1244
Presample missing value lagged residuals set to zero.

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 3.64E-05 | 0.000688 | 0.052996 | 0.9577 |
| AR(1) | -0.003205 | 0.009461 | -0.338750 | 0.7349 |
| MA(1) | 0.012420 | 0.019945 | 0.622680 | 0.5336 |
| RESID(-1) | -0.069340 | 0.031815 | -2.179490 | 0.0295 |
| RESID(-2) | 0.014225 | 0.031032 | 0.458380 | 0.6468 |

| | | | |
|---|---|---|---|
| R-squared | 0.004603 | Mean dependent var | 3.69E-06 |
| Adjusted R-squared | 0.001389 | S.D. dependent var | 0.005461 |
| S.E. of regression | 0.005457 | Akaike info criterion | -7.579653 |
| Sum squared resid | 0.036902 | Schwarz criterion | -7.559050 |
| Log likelihood | 4719.544 | Hannan-Quinn criter. | -7.571906 |
| F-statistic | 1.432291 | Durbin-Watson stat | 1.999084 |
| Prob(F-statistic) | 0.221011 | | |

*Breusch-Godfrey autocorrrelation test the null hypothesis that there is no autocorrelation in the residuals. As the results shows, the *p-value* is insignificant at both 1% and 5% significance level respectively, hence the null hypothesis cannot be rejected, indicating that there is no autoorrelation in the residuals of the third sub sample.

## Appendix B4a: Test for Autocorrelation - Ljung Box

Entire Sample: 2002-2009

Date: 05/05/14 Time: 12:42
Sample: 1 1975
Included observations: 1974
Q-statistic probabilities adjusted for 2 ARMA terms
Null hypothesis: Autocorrelation coefficients are jointly zero (1%)

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| \| \| | \| \| | 1 | -0.035 | -0.035 | 2.3775 | |
| \| \| | \| \| | 2 | 0.006 | 0.004 | 2.4412 | |
| \| \| | \| \| | 3 | -0.015 | -0.014 | 2.8599 | 0.091 |
| \| \| | \| \| | 4 | -0.042 | -0.043 | 6.4013 | 0.041 |
| \| \| | \| \| | 5 | -0.027 | -0.030 | 7.8622 | 0.049 |

*Ljung Box Q statistic tests the null hypothesis that autocorrelation coefficients are jointly zero at 1% significance level. This null hypothesis cannot be rejected for the first five lags of the entire sample period spanning 2002-2009.

## Appendix B4b: Test for Autocorrelation - Ljung Box

Sample 1: 2002-2006

Date: 05/02/14 Time: 17:02
Sample: 1 1230
Included observations: 1230
Null hypothesis: Autocorrelation coefficients are jointly zero (1%)

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| \| \| | \| \| | 1 | -0.039 | -0.039 | 1.8728 | 0.171 |
| \| \| | \| \| | 2 | 0.042 | 0.041 | 4.0813 | 0.130 |

*Ljung Box Q statistic tests the null hypothesis that autocorrelation coefficients are jointly zero at 1% significance level. This null hypothesis cannot be rejected for the first two lags of the first sub sample period spanning 2002-2006.

## Appendix B4c: Test for Autocorrelation - Ljung Box

Sample 2: 2003-2007

Date: 05/02/14 Time: 17:09
Sample: 1 1231
Included observations: 1231
Null hypothesis: Autocorrelation coefficients are jointly zero (1%)

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| \| \| | \| \| | 1 | -0.006 | -0.006 | 0.0494 | 0.824 |
| \|* \| | \|* \| | 2 | 0.097 | 0.097 | 11.679 | 0.003 |

*Ljung Box Q statistic tests the null hypothesis that autocorrelation coefficients are jointly zero at 1% significance level. This null hypothesis cannot be rejected for the first two lags of the second sub sample period spanning 2003-2007.

## Appendix B4d: Test for Autocorrelation - Ljung Box

Sample 3: 2004-2008

Date: 05/02/14 Time: 17:17
Sample: 1 1245
Included observations: 1245
Null hypothesis: Autocorrelation coefficients are jointly zero (1%)

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| \| \| | \| \| | 1 | 0.061 | 0.061 | 4.6727 | 0.031 |
| \|* \| | \|* \| | 2 | 0.137 | 0.133 | 27.994 | 0.000 |

*Ljung Box Q statistic tests the null hypothesis that autocorrelation coefficients are jointly zero at 1% significance level. This null hypothesis cannot be rejected for the first two lags of the third sub sample period spanning 2004-2008.

## Appendix B5a: Heteroskedasticity Test - ARCH Effects

Entire Sample: 2002-2009

Heteroskedasticity Test: ARCH
Null hypothesis: all *q* lags of the squared residuals have coefficient values that are not significantly different from zero

| | | | |
|---|---|---|---|
| F-statistic | 1.350326 | Prob. F(5,1963) | 0.2403 |
| Obs*R-squared | 6.749054 | Prob. Chi-Square(5) | 0.2400 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/05/14 Time: 12:44
Sample (adjusted): 7 1975
Included observations: 1969 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 2.29E-05 | 5.04E-06 | 4.540230 | 0.0000 |
| RESID^2(-1) | 0.042916 | 0.022570 | 1.901426 | 0.0574 |
| RESID^2(-2) | 0.027701 | 0.022583 | 1.226594 | 0.2201 |
| RESID^2(-3) | -0.004430 | 0.022592 | -0.196073 | 0.8446 |
| RESID^2(-4) | 0.026134 | 0.022583 | 1.157221 | 0.2473 |
| RESID^2(-5) | -0.004779 | 0.022570 | -0.211746 | 0.8323 |

| | | | |
|---|---|---|---|
| R-squared | 0.003428 | Mean dependent var | 2.51E-05 |
| Adjusted R-squared | 0.000889 | S.D. dependent var | 0.000217 |
| S.E. of regression | 0.000217 | Akaike info criterion | -14.02695 |
| Sum squared resid | 9.27E-05 | Schwarz criterion | -14.00993 |
| Log likelihood | 13815.53 | Hannan-Quinn criter. | -14.02070 |
| F-statistic | 1.350326 | Durbin-Watson stat | 1.998758 |
| Prob(F-statistic) | 0.240291 | | |

*Checking ARCH effects in the entire sample data involves undertaking a heteroskedasticity test with the null hypothesis that all *five* lags of the squared residuals have coefficient values that are not significantly different from zero. The *p-value* of the F-statistic,0.2403, shows that the null hypothesis cannot be rejected at 1% significance level. Failure to reject the null hypothesis indicates lack of eveidence for the existence of the ARCH effects. Lagrange multiplier statistic is also highly statistically signicant at 1% significance level suggesting that volatility is not time varying.

## Appendix B5b: Heteroskedasticity Test - ARCH Effects

Sample 1: 2002-2006

Heteroskedasticity Test: ARCH

Null hypothesis: all *q* lags of the squared residuals have coefficient values that are not significantly different from zero

| | | | |
|---|---|---|---|
| F-statistic | 0.125661 | Prob. F(5,1218) | 0.9866 |
| Obs*R-squared | 0.631072 | Prob. Chi-Square(5) | 0.9865 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/13/14 Time: 14:58
Sample (adjusted): 7 1230
Included observations: 1224 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 2.43E-05 | 7.70E-06 | 3.155175 | 0.0016 |
| RESID^2(-1) | 0.012377 | 0.028653 | 0.431941 | 0.6659 |
| RESID^2(-2) | -0.001399 | 0.028651 | -0.048816 | 0.9611 |
| RESID^2(-3) | -0.003700 | 0.028650 | -0.129135 | 0.8973 |
| RESID^2(-4) | 0.018600 | 0.028651 | 0.649194 | 0.5163 |
| RESID^2(-5) | -0.002575 | 0.028661 | -0.089839 | 0.9284 |

| | | | |
|---|---|---|---|
| R-squared | 0.000516 | Mean dependent var | 2.49E-05 |
| Adjusted R-squared | -0.003587 | S.D. dependent var | 0.000263 |
| S.E. of regression | 0.000264 | Akaike info criterion | -13.63836 |
| Sum squared resid | 8.47E-05 | Schwarz criterion | -13.61331 |
| Log likelihood | 8352.676 | Hannan-Quinn criter. | -13.62893 |
| F-statistic | 0.125661 | Durbin-Watson stat | 1.999133 |
| Prob(F-statistic) | 0.986641 | | |

*Checking ARCH effects in the first sub sample data involves undertaking a heteroskedasticity test with the null hypothesis that all *five* lags of the squared residuals have coefficient values that are not significantly different from zero. The *p-value* of the F-statistic,0.9866, shows that the null hypothesis cannot be rejected at both 1% and 5% significance level, respectively. Failure to reject the null hypothesis indicates lack of eveidence for the existence of the ARCH effects. Lagrange multiplier statistic is also highly statistically signicant at both 1% and 5% significance level suggesting that volatility is not time varying.

## Appendix B5c: Heteroskedasticity Test - ARCH Effects

Sample 2: 2003-2007

Heteroskedasticity Test: ARCH

Null hypothesis: all *q* lags of the squared residuals have coefficient values that are not significantly different from zero

| | | | |
|---|---|---|---|
| F-statistic | 0.179547 | Prob. F(5,1219) | 0.9703 |
| Obs*R-squared | 0.901488 | Prob. Chi-Square(5) | 0.9701 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/13/14 Time: 15:00
Sample (adjusted): 7 1231
Included observations: 1225 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 2.78E-05 | 8.05E-06 | 3.455039 | 0.0006 |
| RESID^2(-1) | 0.009313 | 0.028642 | 0.325163 | 0.7451 |
| RESID^2(-2) | 0.019033 | 0.028640 | 0.664567 | 0.5065 |
| RESID^2(-3) | -0.006149 | 0.028644 | -0.214679 | 0.8301 |
| RESID^2(-4) | 0.015479 | 0.028640 | 0.540473 | 0.5890 |
| RESID^2(-5) | -0.001678 | 0.028647 | -0.058565 | 0.9533 |

| | | | |
|---|---|---|---|
| R-squared | 0.000736 | Mean dependent var | 2.88E-05 |
| Adjusted R-squared | -0.003363 | S.D. dependent var | 0.000274 |
| S.E. of regression | 0.000274 | Akaike info criterion | -13.55852 |
| Sum squared resid | 9.18E-05 | Schwarz criterion | -13.53349 |
| Log likelihood | 8310.596 | Hannan-Quinn criter. | -13.54910 |
| F-statistic | 0.179547 | Durbin-Watson stat | 1.999484 |
| Prob(F-statistic) | 0.970330 | | |

*Checking ARCH effects in the second sub sample data involves undertaking a heteroskedasticity test with the null hypothesis that all *five* lags of the squared residuals have coefficient values that are not significantly different from zero. The *p-value* of the F-statistic,0.9703, shows that the null hypothesis cannot be rejected at both 1% and 5% significance level, respectively. Failure to reject the null hypothesis indicates lack of eveidence for the existence of the ARCH effects. Lagrange multiplier statistic is also highly statistically signicant at both 1% and 5% significance level suggesting that volatility is not time varying.

## Appendix B5d: Heteroskedasticity Test - ARCH Effects

Sample 3: 2004-2008

Heteroskedasticity Test: ARCH

Null hypothesis: all *q* lags of the squared residuals have coefficient values that are not significantly different from zero

| | | | |
|---|---|---|---|
| F-statistic | 0.796356 | Prob. F(5,1233) | 0.5523 |
| Obs*R-squared | 3.988277 | Prob. Chi-Square(5) | 0.5511 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/13/14 Time: 15:01
Sample (adjusted): 7 1245
Included observations: 1239 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 2.75E-05 | 7.82E-06 | 3.513095 | 0.0005 |
| RESID^2(-1) | 0.046848 | 0.028478 | 1.645036 | 0.1002 |
| RESID^2(-2) | 0.020707 | 0.028502 | 0.726514 | 0.4677 |
| RESID^2(-3) | -0.003451 | 0.028508 | -0.121068 | 0.9037 |
| RESID^2(-4) | 0.022158 | 0.028502 | 0.777408 | 0.4371 |
| RESID^2(-5) | -0.004294 | 0.028478 | -0.150779 | 0.8802 |

| | | | |
|---|---|---|---|
| R-squared | 0.003219 | Mean dependent var | 2.99E-05 |
| Adjusted R-squared | -0.000823 | S.D. dependent var | 0.000268 |
| S.E. of regression | 0.000268 | Akaike info criterion | -13.60777 |
| Sum squared resid | 8.84E-05 | Schwarz criterion | -13.58297 |
| Log likelihood | 8436.016 | Hannan-Quinn criter. | -13.59845 |
| F-statistic | 0.796356 | Durbin-Watson stat | 1.998852 |
| Prob(F-statistic) | 0.552271 | | |

*Checking ARCH effects in the thrid sub sample data involves undertaking a heteroskedasticity test with the null hypothesis that all *five* lags of the squared residuals have coefficient values that are not significantly different from zero. The *p-value* of the F-statistic,0.5523, shows that the null hypothesis cannot be rejected at both 1% and 5% significance level, respectively. Failure to reject the null hypothesis indicates lack of eveidence for the existence of the ARCH effects. Lagrange multiplier statistic is also highly statistically signicant at both 1% and 5% significance level suggesting that volatility is not time varying.