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MODELLING VOLATILITY AND ESTIMATION OF THE MARKET RISK USING MONTHLY RETURNS OF TOP 10 INDEX. A STUDY AT ZIMBABWE STOCK EXCHANGE

BY

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APPROVAL FORM

I Rangarirai N Mutamba do hereby declare that this submission is my own work apart from the references of other people's work, which has duly been acknowledged. I hereby declare that this work has been presented neither in whole nor in part for any degree at this university or elsewhere.

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Chairperson	Signature	Date

DEDICATION

To my lovely family.

Acknowledgement

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Abstract

Market risk, Operational risk and Credit risk are the major categories of financial risk. Market risk is the risk of losses on financial investments caused by extreme price movements in stocks, changes in commodities prices, interest rates and exchange rate fluctuation and economic recessions and affects the entire market. Volatility models helps to anticipate the market risk (volatility) and expected returns. Financial institutions and regulatory committee can also use the Volatility models set margins of potential loss that is risk management using value at risk (VAR). The researcher derived an optimal model using Conditional Heteroscedasticity GARCH type models for ZSE.

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Acronyms

ZSE	Zimbabwe Stock Exchange
TGARCH	Threshold Generalized Autoregressive Conditional Heteroscedasticity
EGARCH	Exponential Generalized Autoregressive Conditional Heteroscedasticity
ARCH	Autoregressive Conditional Heteroscedasticity
AR	Autoregressive
RTGS	Real -Time Gross Settlement
RBZ	Reserve Bank of Zimbabwe
VAR	Value at Risk
PACF	Partial Autocorrelation Function
AIC	Akaike Information Criteria
ACF	Autocorrelation Function

1. CHAPTER 1: INTRODUCTION

1.1 Introduction

Financial markets is a market in which financial securities and derivatives are traded at a low cost. Option, future forwards and swaps, and securities includes bonds, stocks, and commodities trades at these markets. According to Berk and DeMarzo (2017), stock markets provide liquidity and determine the market price for the company's share. An investment is said to be liquid if it is possible to sell it quickly at a price very close to the price at which you could contemporaneously buy it, (Berk and DeMarzo 2017). Well-developed and smoothly operating financial markets contribute to the health and efficiency of the economy. Financial markets are critical in accumulation of capital for the production of goods and services, research and development of products, and for Innovation. It major source of capital to Government and large corporation.

Volatility, which is commonly measured by the standard deviation of the returns has received a greater attention in literature. It is a key factor in portfolio theory, option valuation, asset pricing models and formulation of the economic policies and rules relating to the stock market. Volatility of stock market can be a source of concern because the instability of stock markets creates uncertainty that can affect growth prospects.

The univariate volatility models include the autoregressive conditional heteroscedastic (ARCH) model of Engle (1982), the generalized ARCH (GARCH) model of Bollerslev (1986), are used to model volatility of assets returns. The sophisticated exponential GARCH (EGARCH) model of Nelson (1991), the threshold GARCH (TGARCH) model of Glosten, Jagannathan, and Runkle (1993) and Zakoian (1994), these models seeks to improve the GARCH model in capturing the characteristics of assets returns.

1.2 Background of research

Tsay(1995) claims that if one accepts the claim that stock prices are governed by the econometric models such as the Black Sholes formula one can use the formula to calculate the conditional standard deviation(*implied volatility)* of the underlying stock. Tsay justifies that implied volatility calculated using the Black Scholes formula tends to be larger than obtained using GARCH type volatility models because of risk premium and the way in which the daily return are calculated.

Volatility (conditional standard) deviation has important implication on options trading. Consider for example the price of the European *call option*, which gives the holder of the option the right but not obligation to buy fixed number of shares of a specified common stock at fixed date on a given date. The price of an option given by the well-known Black Scholes option pricing formula states that the price of such call option is

$$c_t = P_t \emptyset(x) - Ke^{-rl}\emptyset\left(x - \sigma_t\sqrt{l}\right), and\ x = \frac{lin\left(\frac{Pt}{K}\right) + rl}{\sigma_t\sqrt{l}} + \frac{1}{2}\sigma_t\sqrt{l}$$

Where P_t the current price of the underlying stock, r is the continuously compound risk free interest, σ is the annualized conditional standard deviation of the log return of a specific stock, k is the strike price and $\emptyset(x)$ is the cumulative distribution function of the standard normal function evaluated at x. It is suffices here to say that conditional standard deviation of the underlying stock plays an important role. This volatility evolves over time.

Market risk, Operational risk and Credit risk are the major categories of financial risk. Market risk is the risk of losses on financial investments caused by extreme price movements in stocks, changes in commodities prices, interest rates and exchange rate fluctuation and economic recessions and affects the entire market. Introduction of the new currency on 21 February 2019 as the new monetary policy measures which states establishment of an interbank Foreign Exchange market. The denomination of the existing RTGS balances, bond notes and coins in circulation as RTGS dollars in order to establish an exchange rate between the RTGS dollars and foreign currency. Together with the removal of the multiple currency, system through Statutory Instrument (SI) 142 in June 2019 caused a greater stability in exchange rate with the RTGS deteriorating in value (RBZ monetary polies, 2019). Due to this new monetary policy, the inflation rises with an annual inflation of 225.29% in 2019 up from 10.61% in 2018 and reach a climax of 557.21% in 2020 rampaged the economy. Increased inflation rate, price distortions, exchange rate and interest rate fluctuation increased the uncertainty in market volatility for stock on ZSE. Value at risk (VAR) has become a standard measure of market risk in risk management but it is still applicable to other types of risk. Econometrics modeling using volatility models, Risk Metrics and Extreme value theory are some of the methods used to calculate value at risk (VAR). Furthermore, modelling volatility of a time series can improve the efficiency in parameter estimation and in interval forecast, Tsay (1995).

Beta of the capital asset pricing model (CAPM) is calculated using Market risk (systematic risk). Beta is a measure of the volatility of the individual stock compared to the systematic risk, and approximates risk that a stock will add to a portfolio.

1.3 Zimbabwe stock exchange: an overview.

Zimbabwe stock exchange (ZSE) is a financial market on which trading of assets takes place, assets such as equities (stocks), bonds, currencies trades at ZSE. ZSE was founded in 1946 and it is a licensed security in terms of the security and exchange act (24:25). ZSE core mandatory is to facilitate long-term capital raising through listing of securities as well as offering secondary market securities trading and issuer regulation services. There are 63 companies listed at ZSE and a domestic market capitalization of 8,288 million US$. There are four indices, namely All Share index, Top ten index, Industrial index and the Mining Index. ZSE does manual trading on weekdays call over that begins at 9.00am and noon. The roles of the ZSE are to facilitate raising to long-term capital for companies, government and semi-government institutes. Providing a regulated platform for secondary market buying and selling of securities and information such as historical financials, securities and markets reports. ZSE supervises and monitor the trading process to ensure transparency in the market and that no unfair practices are done to manipulate the market. Any off market deals and any unethical criminal activities like inside are dealt with within the framework of the rules and regulations governing the stock market transactions in Zimbabwe

1.4 **Problem statement**

The general idea about the GARCH type volatility models is that it should be able to capture the volatility characteristics that is volatility clustering; volatility is mean reverting and leverage effect (risk premium effect). The key part of volatility models is that it should be able to forecast volatility and provide an overview of the future returns to the investors. The volatility models forecast, predict the quantile, or the entire density and such density are important in risk management, derivative pricing and hedging, portfolio selection, market timing and market making. In each, the predictability of the volatility that is required. In making financial decisions investors and decision makers should have a more guideline and able to assess risk involved. The aim of the study is to find out the best model to use in predicting the volatility of Top 10 index monthly returns on Zimbabwe stock exchange (ZSE).

1.5 **Aim**

The aim of the study is to examine the best method for forecasting volatility between the symmetric and the asymmetric GARCH models for the Top 10 index at the Zimbabwe stock exchange. Estimation of Value at risk (VAR) to enable investor and financial institution in the management of risk.

1.6 **Objectives**

- To estimate the market risk involved of stock listed on Zimbabwe stock exchange.
- To identify an optimal/best model for modelling volatility of stocks returns.
- To forecast index returns and volatility of the index returns using GARCH models.
- To estimate Value at Risk (VAR).

1.7 **Research questions**

What is the best model that can model volatility of the stocks on ZSE?

What is the market risk of investing on ZSE and how did the market risk evolves during the transitional period.

1.8 Scope of the study

The efforts of the study is to determine the best methods between the symmetric GARCH models and the asymmetric GARCH models of modelling volatility of Top 10 index on ZSE. Through analyzing data of stocks returns listed on Top ten index on Zimbabwe Stock Exchange using R package, the researcher will be able to identify an optimal model. The monthly returns of Top 10 index from November 2018 to October 2021. The aim of the study is to formulate an optimal function that calculates the conditional standard deviation (implied volatility) for the past returns and to forecast the volatility.

1.9 The significant of the study

The main objectives of the study is to choose an optimal function that estimate the conditional standard deviation and forecast of the volatility and projects how it affects investor's decision and the model could be used by investors to forecast on volatility and returns of Top 10 index. Forecasting of market risk (volatility) and returns using the GARCH type model could help financial institution and regulatory committee to set margins of potential loss risk management using value at risk (VAR). The forecasting of volatility also helps different investors to speculate, anticipates the stock's price movements, and take a future position in expecting to make profits. Individual can use the market risk to calculate $beta$ of individual stock, and then assess the performance of the different stocks.

1.10 Assumption of the study

All investor are rational

Market efficiency

Volatility clustering

"Leverage" effect

1.11 Limitation of the study.

The study only use data from Zimbabwe dollar leading to a small sample, which may leading to the deviation of the results from the actual result.

The study only into account the Top ten index returns.

1.12 Definition of terms

- Market risk- also known as systematic risk, it mainly influenced by external factors on an organization, deemed as uncontrollable from an organizational perspective. It is a fluctuation in return on securities that occur due to macroeconomic factors.

- Operational risk-is the risk of loss resulting from ineffective internal process that is people systems, and external events that could disrupt the flow of business operations.

- Conditional standard deviation (volatility) - volatility is the measurement of risk. Higher volatility leads to large variation of return, hence higher risk.

- Option- is contract that gives the holder the right but not obligation to buy and sell an underlying stock at a specified date and time.

- Volatility clustering- a volatility characteristic which states that volatility may be higher for certain periods and low for other periods.

- Leverage effect- a volatility characteristics which states that volatility reacts differently to big prices increase and big price drops.

- Hedging-is an attempt to reduce exposure to risk through taking of opposite position in a risk asset. The essence of hedging strategy is the adoption of a futures position that, on average, generates profits when the market value of the commitment is higher than the expected value leading to reduced profits.

1.13 Chapter summary

This chapter give an overview of the importance of volatility study in financial application, outlining the background, problem statement, research objectives and the scope of the study. It also introduces the estimation of VAR using econometrics methods that is conditional heteroscedasticity models.

2. CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

A literature review is the contextualization of accumulated relevant knowledge from published works (Gwimbi and Dirwai 2003). White (2005) regards literature review as interpretation of what is ready to add value to own writing. Literature review is the scholarly writing directly related to your research.

The study of volatility of stock market links to the risk of underlying assets. Volatility of prices reflects the uncertainty in markets. Higher volatility leads to large variations of return, hence higher risk. Therefore, volatility of stock market provide a useful information in measuring risk. Many theories have been to describe the behavior of volatility and models forecasts on the stock market movement and evaluating the performance of the stock market. The stock market plays a pivotal role in today's economic activities; it acts as a measure and awareness for the economy and financial activities. Many studies show that random walk model is superior in explaining the stock market movement. However, recent studies reveal results that stock market deviate from random walk behavior.

Individual and institutional investors are concerned with the risk and returns on their investments. Therefore, a clear understanding of market and security volatility becomes more significant among investors in recent studies. The flow of information influence investor's decisions and relates closely with volatility of stock prices. In this chapter, the researcher aims to understand the characteristics of volatility and the volatility model used to capture these characteristics that is the symmetric and asymmetric GARCH model with evidence of the survey from literatures made available.

2.2 Theoretical Framework

2.2.1 Causes for volatility of prices in stock market

From the theoretical front, the stock market have fluctuating stock price which exhibit volatility; bringing variation in the returns of the investor's investment. The prices of the stocks changes every day when the buyers and sellers are actively participating with the intension of making some returns. Psychological issues that is supply and demand (liquidity) and the uncertainty of the company's future affects stock price movements and these movements will determine the volatility of stock market.

According to Ramanthan and Gopalakinshan (2013), the availability of new information on the underlying stock, inflation and economic strength of market affects future movements of stock prices. Laakkonen (2008) found that macroeconomic news increase volatility significantly and negative news increase volatility more than positive news. The flow of information is a vital factor in the movements of the stock prices, which is associated with the volatility.

Lipson (1994) investigates the effect of the information flow on the behavior of stock prices and suggests that the public information is the major sources of short-term return volatility. The investors react and interpret to the immediate information, adjusting the market prices up or down leads to high fluctuation (volatility) in the market. Volatility is also associated with trading opportunities and various market and non-market components. Beny and Howe (1994) found relation between public information and trading volumes but an insignificant relationship price volatility. The persistence is the one most significant characteristics of volatility.

2.2.2 Efficiency capital markets theory

The efficient capital market theory was developed by Fama(1960), Efficient market hypothesis is categorized under weak market efficient hypothesis, semi-strong market hypothesis and Strong market hypothesis. An efficiency market is the one in which stock prices always reflect the available information Anupo Rao (2017). The security prices adjust rapidly to the arrival of the new information and therefore current security fully reflect all the available information. Theory supports that stock markets are efficient or close to efficiency. The theoretical view of volatility is behind market efficient hypothesis. An efficient capital market is one in which security prices adjust rapidly to the arrival of new information and therefore the current prices of securities reflect all information about the security. Fama (1970) attempted to formalize the theory and organize the growing empirical evidence. Fama presented the efficient market theory in terms of a fair game model, contending that investors can be confident that a current market price fully reflects all available information about a security and therefore the expected return based upon this price is consistent with its risk.

2.2.3 Weak form hypothesis

According to Reilly and Brown (2011),Weak market hypothesis assumes that the current stock price fully reflect all the market information, including the historical sequence of prices, rates of return, trading volume data, and other market-generated information, such as odd-lot transactions and transactions by market makers. Because it assumes that current market prices already reflect all past returns and any other security market information, this hypothesis implies that past rates of return and other historical market data should have no relationship with future rates of return (that is, rates of return should be independent). Therefore, this hypothesis contends that the investors gain little from using any trading rule, which indicates that you should buy or sell a security based on past rates of return or any other past security market data.

2.2.4 Semi-strong efficient market hypothesis

Reilly and Brown(2011) asserts that in a semi-strong EMH security prices adjust rapidly to the release of all public information that is current security prices fully reflect all public information. The semi-strong hypothesis comprises the weak-form hypothesis because it covers all the market information. Furthermore, public information also includes all nonmarket information, such as earnings and dividend announcements, price-to-earnings (P/E) ratios, dividend-yield (D/P) ratios, price-book value (P/BV) ratios, stock splits, news about the economy, and political news. This hypothesis implies that investors who base their decisions on any important new information after it is public should not derive above-average risk-adjusted profits from their transactions, considering the cost of trading because the security price should immediately reflect all such new public information.

2.2.5 Strong efficient market hypothesis

The strong EMH contends that stock prices fully reflect all information from public and private sources. This means that no group of investors has monopolistic access to information relevant to the formation of prices. Therefore, this hypothesis contends that no group of investors should be able to consistently derive above-average risk-adjusted rates of return. The strong EMH encompasses both the weak and the semi-strong EMH. Further, the strong EMH extends the assumption of efficient markets, in which prices adjust rapidly to the release of new public information.

2.2.6 Volatility clustering

Volatility classical model are useful tools in measuring the risk associated with a security and the entire stock market. ARCH model proposed by Engle (1992) and the Generalized ARCH model proposed by Bollerslev (1986) and Taylor, are amongst the models that captures stock market volatility. The models estimates the variance of the forecasted return based on past forecast errors as well as past estimates of volatility. Nelson (1960), proposed the extension of the volatility models and alternative specifications on the model such as GARCH-M, IGARCH, EGARCH and Threshold GARCH model. These alternative models seek to improve the GARCH model in capturing characteristics of return series.

Rakesh Kumar (2007) examined volatility trend of Indian stock market from 1996 to 2005 by using daily and monthly data of returns. The study observed high volatility during the decline periods (1996-1999) and recession period (2000-2002) period and moderately less volatile during the economic growth (2003-2005) since investor are largely response to economic aspects.

Volatility clustering is the collection of small and large movement's asset prices. According to Bose (2007), the characteristics of return volatilities suggests that large changes of prices(variance of returns) for a period is likely to be followed by large changes, the higher volatility tends to be preceded for a while after initial shock and a period of low volatility is likely to be followed by small changes. Therefore, this means that there exist volatility clustering which states that volatility may be higher in a certain period and lower for other period. In fact, today's volatility shocks will influence the expectation of future's volatility. The underlying stock volatility levels affects the returns of that asset to its mean levels, termed mean reversion. This effect of shocks for the underlying asset will take a long time to recover to its normal level, thus return series is characterized by a level of volatility persistence.

2.2.7 Leverage effect

The leverage effect refers to a well-established relationship between stock returns and both implied and released volatility. Empirical studies found that there is asymmetrical changes in the stock prices for a given event or shock that leads to considerably higher volatility in the stock returns. This means that volatility react differently to a big price increase or a big price drop, referred to as the leverage effect. Investors responds more sensitively to bad rather than good news and this creates a well-known volatility characteristic.

Black (1976) found that leverage on volatility had strong negative correlation between stock price change and volatility response- stock volatility likely to be increase when stock price declines. The leverage effect suggests a decrease in stock price of a company reduces the value of equity comparative to debt and increase the financial leverage. A positive change in financial leverage increases the risk of holding the equities which in turn increase the future volatility.

2.2.8 Volatility and leverage

Schwert (1990) showed that stock market volatility increases during the recessions and after a large drop in stock prices. He found a direct relationship between financial leverage of the market and volatility. For example considering firm with equity in its capital structure under the assumption that the debt is risk free so that changes in the firm value are entirely bone by the stock. Let, $V = E + D$, represents total firm value and $E = NS$ denotes the total current market value of the firm, N represent the outstanding shares of stock with current price S. Suppose there is a random change in overall firm value, as a percentage change in firm value, this is $\frac{\Delta V}{V}$.

All of the changes in firm value will flow through to the stock, so $\Delta E = V$, producing a percentage change in the stock price as follows;

$$\frac{\Delta S}{S} = \frac{\Delta E}{E} = \frac{\Delta V}{V}\frac{V}{E} = \frac{\Delta V}{V}(\frac{E + D}{E}) = \frac{\Delta V}{V}(1 + \frac{D}{E})$$

The percentage change in stock price is equal to the percentage change in firm value times one plus the debt equity ratio. The leverage the firm is (high $\frac{D}{E}$) the more volatile the will be relative to the total firm. That is expressed as follows.

$$\sigma_S = \sigma_E = \sigma_{VL}$$

If σ_V is constant, then the stock volatility, σ_S will rise when the stock prices goes down and fall when it goes up. Hence, the empirically observed connection between stock returns and volatility changes is understandable and consistent with the established principles of modern finance.

2.2.9 Value at Risk (VAR)

According to Duffie and Pan (1997) and Jorion (2006), VAR is a single estimate of the amount by which an institution's position in a risk category could decline due to general market movements during a given period. Financial institutions and investors can use VAR to assess their risks or by a regulatory committee to set margin requirements for an investment. In addition, it ensures that the financial institutions can be still be in the business after a catastrophic event.

2.2.10 Inflation

Culberson (2003) highlight that when inflation increases, purchasing power declines and each dollar can buy fewer goods and services. For investors interested in income-generating stocks, or stocks that pay dividends, the impact of high inflation makes these stocks less attractive than during low inflation, since dividends do not keep up with inflation levels. Dusak (2009) further indicated that lowering purchasing power, the taxation on dividends causes a double-negative effect. Despite not keeping up with inflation and taxation levels, dividend-yielding stocks do provide a partial hedge against inflation.

2.2.11 Expected shortfall

Expected shortfall is a risk measure concept used in field of financial risk management to evaluate the market risk and the credit risk of the portfolio. In application, the actual loss can be greater than VAR, to overcome VAR weakness one can consider the expected shortfall function.

$$E(S) = u_t + \frac{f(x_q)}{q}\sigma_t, f(x) = {}^{1}\!/_{\sqrt{2\pi}} \exp(-x^2/2)$$

2.3 Empirical Literature

Empirical studies applied the symmetric and asymmetric GARCH model in capturing the stock market volatility and these studies cover different countries. The studies focuses on stock markets in developed and developing countries.

Some studies report that asymmetric GARCH type model are the best model for forecasting stock market volatility. Liu et al (2009) investigated the forecast of stock market volatility in china using the GARCH model and found that volatility forecast by the GARCH-SGED model are more accurate than those generated using the GARCH-N model, indicating the significant of both skewness and tail thickness in the conditional distribution of returns, especially for emerging financial markets. The GARCH-SGED models yields lower MSE and MAE and generates superior volatility forecast.

Alberga et al (2008) investigated the stock market volatility in Israel using GARCH model. The result show that asymmetric GARCH model with fat-tailed densities improves overall estimation for measuring conditional variance. The results shows that the asymmetric GARCH type models improves forecast performance. Among the forecast tested the EGARCH with a skewed student-t distribution outperformed GARCH, GJR GARCH models.

Lim and Sek (2013) conducted a comparative analysis between asymmetric and symmetric GARCH type models, evaluating the forecast performance and the capability of the models in capturing volatility of stock market in Malaysia. The researcher divided data into three sub-periods that is pre-crisis, crisis and post-crisis periods. The results showed that the performance of these models vary across periods and error measurement methods. Symmetric GARCH type model performed better during the crisis period while asymmetric TGARCH model did better during the pre and post crisis periods.

A study conducted by Wong and Kok (2005) reveals that ARCH and random walk is the superior model to capture the stock market's volatility. The study compared the forecasting models for ASEAN stock markets (Malaysia, Singapore, Thailand Indonesia and Philippines). The results indicated that the remaining two markets are the best modelled by the random walk model that is Indonesia and Philippines. The fond that in the post crisis period TGARCH and EGARCH models are the most suitable models. The asymmetry of the market returns is not significant in all the markets modeled by the TGARCH and EGARCH models.

Mike and Philip (2006) evaluated the GARCH model in estimation of VAR, including the Risk Metrics and long memory models. The models were applied to market indices and exchange rate accessing each model in estimation of VAR. the results showed that both stationary and fractional integrated GARCH models outperformed Risk Metrics in estimation of VAR.

Hansen and Lunde (2005) compared the ARCH-type models in terms of the ability of the models to describe the conditional variance using out-of-sample data. The Exchange rate and IBM data were used in their study. The researcher found no evidence that GARCH (1,1) was outperformed by sophisticated methods in analysis of Exchange rate data whereas the GARCH(1,1) was inferior to asymmetric GARCH type models that accommodates leverage effect.

The study carried by Nugroho and Kurniawati (2019) in comparison between asymmetric and symmetric GARCH type models based on S&P 500 and Nifty indices data indicated that symmetric GARCH type models were out performed by the sophisticated asymmetric GARCH models. The study indicated that T GARCH model provided the best fitting.

In evaluating the performance of models, studies apply different evaluation measures. The widely applied measures include Mean Square Error (MSE), Root Mean Square Error (RMSE) and absolute perfect error (MAPE). In practice the comparing the different models it is rarely the case that one model dominate the other with respect to all evaluation measures. The common way to solve the problem is to carry out the average figures of some statistical measures and then compare the forecast models based on parameter obtained.

2.4 Chapter summary

This chapter focuses on empirical study of volatility and different authors views on volatility modelling. It indicated the use of different volatility model in different markets.

3. CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

According to Kothari C.R (2004), research methodology is a way to systematically solve the research problem as well as the science of studying how research is done scientifically. In this chapter, the researcher points out methods adopted to solve the research problem along with the logic behind them.

3.2 Research design

A research design is the arrangement of conditions for collection and analysis of data in a manner that aims to combine relevance to the research purpose with economy in procedure, Kothari (2004). In fact, a research design is a conceptual framework within which research is conducted; it constitutes the blueprint collection, measurement and analysis of data.

3.3 Research instrument

Research instruments are tools for data collection. The data was analyzed using R programming software version 4.0.5. The researcher also used textbook, reading of published documents and journals to provide literature review, theories and basic information. The researcher obtained data used in the research from the internet, the researcher access closing price of Top 10 index from m.investing.com.

3.4 Data collection

The study used secondary data on firms listed on the Zimbabwe Stock Exchange. According to Boslaugh (2007), Secondary data refers every dataset not obtained by the author or the analysis of data gathered by someone. Secondary data includes data previously gathered and could be used to answer new questions, for which the data gathered was not originally intended, Vartainian (2010). Data collection is important in assembling the required information with an aim of achieving the research objective. The researcher obtained data from m.investing.com website, the data contains monthly price of Top 10 index and then converts the data into monthly returns. Normally security prices are nonstationary due to fact that there is no fixed level of price and can be modeled using random-walk models. The study population comprised of top ten counters listed under Top ten index on ZSE which includes Delta, Unifreight, Proplastic, TLS and Lafarge to mention a few. The study period of interest was two years from October 2018 to October 2021

3.5 Weak efficient market hypothesis test

The researcher used statistical test for between rates of returns. EMH contends that security returns overtime should be independent of one another because information come to the market at random and in independent fashion, and the security prices adjust rapidly to the new information. An autocorrelation test was used to test for the EMH.

3.6 Data analysis.

Data analysis involves transforming and modelling of data with the purpose of discovering and identify relationships to support research conclusion. The researcher is going to use monthly return of Top 10 index to model risk that is identify its behavior and characteristics and to estimate and forecast the volatility using Conditional Homoscedasticity models. Modeling and estimation of market risk of ZSE was performed using data of Top 10 return from November 2018 to October 2021

3.7 Conditional Heteroscedasticity models.

3.7.1 Model assumptions

Let r_t be the log return of assets return at time index t. The basic idea behind volatility study is the series $\{r_t\}$ is either serially uncorrelated or within low order serial correlated but it is a dependent series. The volatility model try to capture the dependence in return series.

3.7.2 The ARCH effects

The dependence of the return series is the ARCH effect. Let $a_t = r_t - u_t$ be the residual mean equation. The square shock a_t^2 then used to test for the conditional heteroscedasticity, which also known as the ARCH effect. Lagrange multipliers test of Engle (1982) and Ljung-Box test are the two test available check for the ARCH effect.

3.7.3 The ARCH model

The model of Engle (1982) for modelling volatility of assets returns, the basic idea of the model is that:

(a) The shock a_t of an asset return is serially uncorrelated, but dependent.

(b) The dependence of a_t can be described by a simple quadratic function of its lagged values.

$ARCH(m)$Model

$$a_t = \sigma_t \varepsilon_t \qquad \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \cdots \alpha_m a_{t-m}^2$$

Where $\{\alpha_t\}$ is a sequence of independent and identically distributed random variables with mean zero and variance 1, $\alpha_0 > 0$, and $\alpha_i \geq 0$ for $i > 0$. The coefficients α_i must satisfy some regularity conditions to ensure that the unconditional variance of a_t is finite.

3.7.4 **Model weaknesses:**

- The model assumes that positive and negative shocks have the same effects on volatility because it depends on the square of the previous shocks. In practice, the price of a financial asset responds differently to positive and negative shocks.
- The ARCH model is rather restrictive. For instance, α_1^2 of a $ARCH(1)$ model must be in the interval [$0, \frac{1}{3}$] if the series has a finite fourth moment. The constraint becomes complicated for higher order ARCH models. In practice, it limits the ability of ARCH models with Gaussian innovations to capture excess kurtosis.
- The ARCH model does not provide any new insight for understanding the source of variations of a financial time series. It merely provides a mechanical way to describe the behavior of the conditional variance. It gives no indication about what causes such behavior to occur.
- ARCH models are likely to over-predict the volatility because they respond slowly to large isolated shocks to the return series

3.7.5 $\boldsymbol{GARCH(1,1)}$

Although the ARCH model is simple, it often requires many to parameters adequately describe the volatility process of an asset return. Bollerslev (1986) proposes a useful extension known as the generalized ARCH (GARCH) model to overwhelm some of the weakness of the ARCH model.

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-2}^2 \quad 0 \leq \alpha_1, \beta_1 \leq 0, (\alpha_1 + \beta_1) \leq 0$$

A large a_{t-1}^2 or σ_{t-1}^2 gives rise to a large σ_{t-1}^2. This means that a large a_{t-1}^2 tends to be followed by another large a_t^2, generating, again, the well-known behavior of volatility clustering in financial time series.

3.7.6 The Threshold GARCH Model

A model proposed by Glosten Jagannathan and Runkle (1993) to model volatility and handle the leverage effects (asymmetric of volatility to positive and negative shocks.)

A $TGARCH\ (m, s)$ model assumes the form

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{s}(\alpha_i + \gamma_1 N_{t-i})a_{t-1}^2 + \sum_{j-1}^{m}\beta_j\sigma_{j-1}^2$$

Where N_{t-i} is an indicator for negative a_t that is $N_{t-i} = 1\, for\ a_t < 0\ or\ otherwise$ where α_i, γ_j and β_j are all nonnegative parameters satisfying conditions similar to those of GARCH models. From the model positive shocks contributes $\alpha_i a_{t-1}^2$, whereas a negative shock has a large impact $(\alpha_i + \gamma_i)\ a_{t-1}^2$. This model use threshold to separate of the past shocks. $EGARCH$ Model of (Nelson 1991) is another model, which can capture the asymmetric characteristic of volatility.

3.8 Chapter summary

In this chapter, the researcher outlines the methodology used to carry out the study. Data collection techniques, research design and the data analysis procedure were highlighted. The following chapter focuses on data representation, analysis and discussion and finally the discussion regarding conclusions and recommendations basing on the findings

4. CHAPTER 4: DATA PRESENTATION, ANALYSIS AND DISCUSSION

4.1 INTRODUCTION

In this chapter, the researcher would analyze the collected for Top ten index returns, and used the symmetric and asymmetric GARCH models to analyze monthly index returns data. R programming software obtained data calculations and the graphical presentation.

4.2 Importing data into R

The data obtained from ZSE top ten index was in excel function and the researcher convert the data into $txt(delimited\ function)$ file format. The researcher use R function ($read.table$) to import data into the system.

4.3 Data preparation

The data obtained were monthly closing price for index and the researcher convert data into monthly log returns using R return function. The monthly log returns for the index were calculated; since log return corresponds to percentage change in the value of financial assets the researcher use the log return in data analysis. In addition, the monthly log returns are simple to obtain.

4.4 Descriptive Statistics

Table 1 below shows the overall a sample of 34 observation from November 2018 to October 2021. A monthly-expected return of 0.0820 and a volatility of 0.2198 that is deviation of expected return from the actual population. The below also shows a maximum monthly return of 0.6349 and a minimum return of -0.3560 for the index.

Table 1: Descriptive statistics for Top index monthly returns

Security	Size	Mean	Standard deviation	Skewness	Excess kurtosis	Minimum	Maximum
Top 10	34	0.0820	0.2178	0.1109	0.2118	-0.3560	0.6349

4.5 The distribution of stock returns

The Jarque-Bera normality test shows that the index returns, and normally distributed is questionable. The test indicates that 1%significant level we reject the normality assumption. In addition, the Shapiro-wilk test agrees with JB test.This corresponds with the empirical distribution of asset returns, which states that stock index returns shows heavy tail.

```
Title:
 Jarque - Bera Normalality Test

Test Results:
  STATISTIC:
    X-squared: 0.0785
  P VALUE:
    Asymptotic p Value: 0.9615
Description:
 Fri Nov 19 00:17:09 2021 by user: user
```

4.6 **Time plot**

Figure 1 below is a time plot and it shows the distribution of the returns series of index. A time plot shows returns against time and the diagram below shows extreme price movements on the given period.

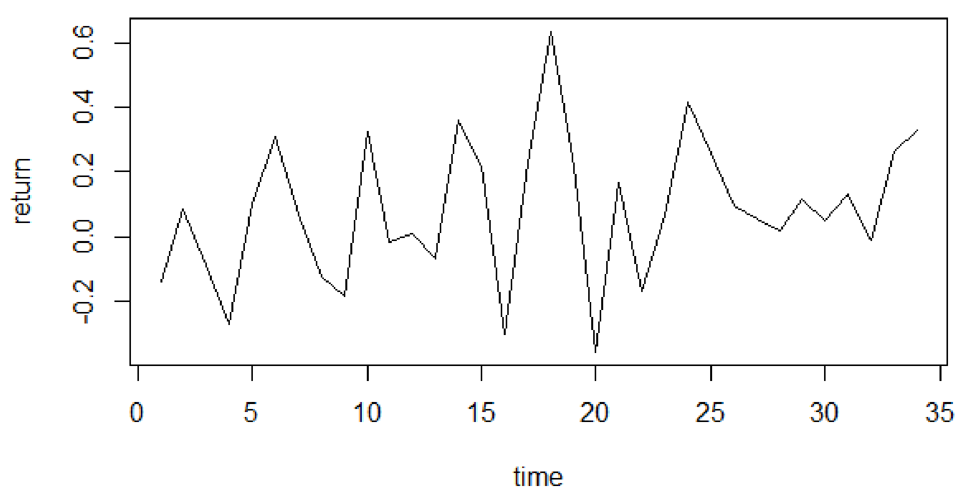

Figure 1 Time plot for the index monthly return

The researcher also used the T test to test the hypothesis of zero expected returns for the index returns. The 95% confidence interval shows that the expected return is positive and the hypothesis of mean equal to zero, we rejected the hypothesis of zero expected return at 1% significant level.

```
One Sample t-test

Data:  lm2
t = 2.1957, df = 33, p-value = 0.03525
Alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
 0.006019532 0.158005471
Sample estimates:
Mean of x
0.0820125
```

4.7 Testing for stationarity assumption

The researcher test for joint serial autocorrelation using Portmanteau statistic. The Box-Ljung test indicating that there is no serial correlation, we fail to reject H_0 at 1% significant level and conclude that monthly index returns are stationary. The test indicates that Top 10 returns are stationary which is good result implies that data is ready for further analysis.

```
Box-Ljung test

data:  lm2
X-squared = 12.833, df = 12, p-value = 0.3813
Alternative hypothesis: there is serial Autocorrelation
```

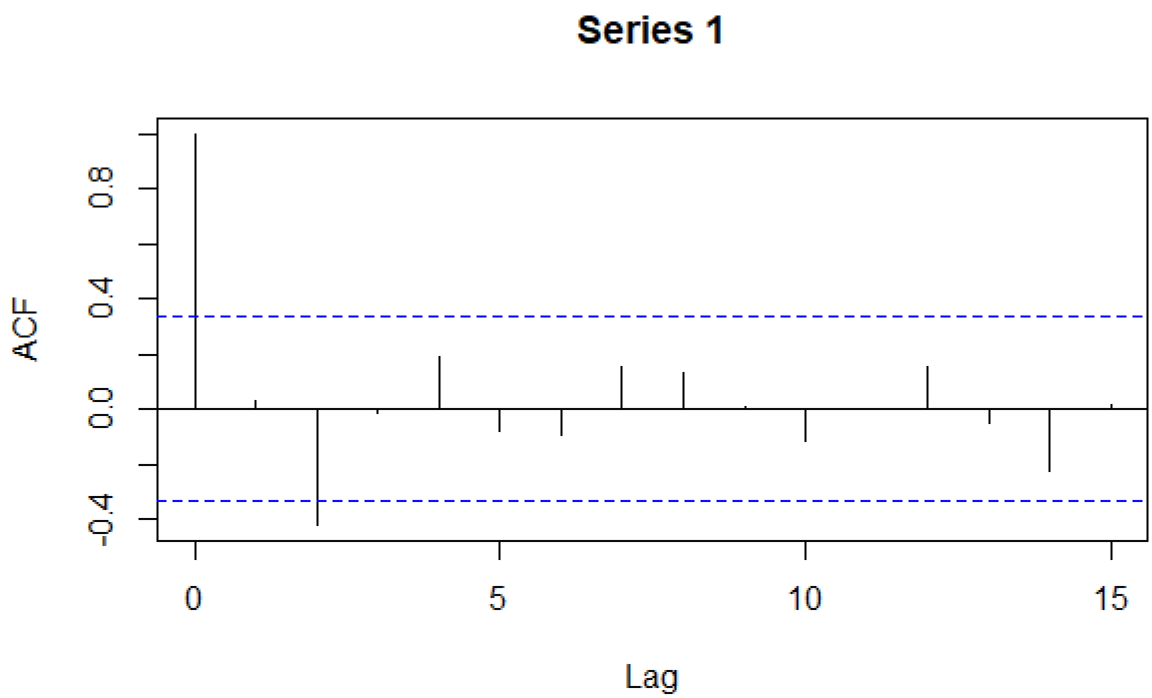

Figure 2 Autocorrelation plot for Top 10 index returns

4.8 Modelling of the stock index volatility

4.9 Testing for the ARCH effect

Let $a_t = r_t - u_t$ be the residual mean equation. The square shock a_t^2 then used to test for the conditional heteroscedasticity, which also known as the ARCH effect. Lagrange multipliers test of Engle (1982) and Ljung-Box test where to test for the ARCH effect. The Lagrange multiplier test shows a strong ARCH effect with the test statistic$F = 80.101$, and a p value close to zero. Top 10 returns shows a strong ARCH effect, which indicates that data can be modelled using conditional heteroscedasticity ARCH model.

```
Lagrange Multiplier test
```

```
Data:  y

LM = 13.067, df = 1, p-value = 0.0003006

Alternative hypothesis: y is heteroscedastic


Box-Ljung test

Data:  y^2

X-squared = 28.423, df = 12, p-value = 0.004795

Alternative hypothesis: y is heteroscedastic
```

4.10 **Oder determination**

The order of a time series model can be determined by using Partial Autocorrelation Function (PACF) or by using the information criteria for example the well- known Alkaike information criterion (AIC), Alkaike (1973).

4.11 **Partial Autocorrelation Function**

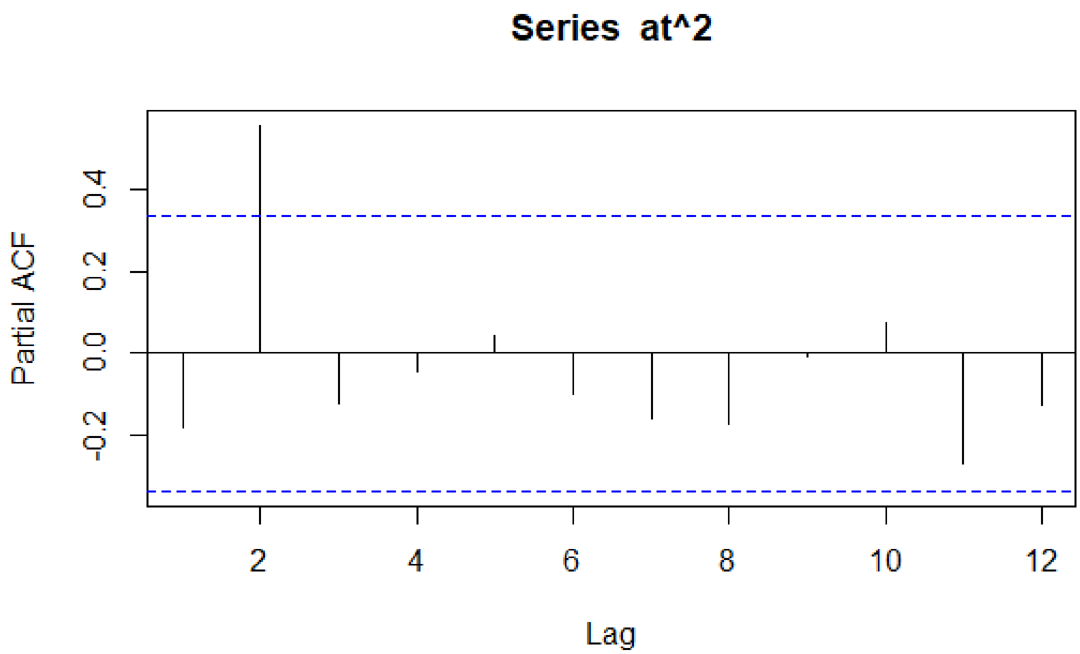

Figure 3 A autocorrelation plot for the residuals

Information criteria can also determine order of the model based on likelihood estimation. Table 2 shows an order 2 that contain a minimum akaike.

Table 2 Alkaike information criteria

Akaike order

0	1	2	3	4	5	6
9.647833	10.5370	0.000000	1.472762	3.407400	5.341876	6.995961

Both AIC and the PACF indicates an ARCH model of order 2. The researcher then continued to model volatility of the returns using an ARCH model of order 2.

4.12 ARCH (2) MODEL

An arch model volatility function and mean equation where obtained using R software from the package $fGARCH$ and α_1 is statistically insignificant and was dropped from the model.

The estimated model is:

$$r_t = 0.0945 + a_t \qquad \sigma_t^2 = 0.0245 + 0.416a_{t-2}^2$$

The researcher use the standardized residuals from the sequence of independent identically distributed random variables to check for model adequacy. The Ljung-Box test statistics of standardized residuals a_t gives $Q(10) = 10.822$ and p value of 0.372 and those of squared standardized residuals a_t^2 gives $Q(10) = 6.342$ and a p value of 0.786. The estimated ARCH (2) model is adequately describing the conditional heteroscedasticity of index returns at 5 % significant. Finally, we can use ARCH model to predict the volatility of the index monthly returns.

Table 3 Standardized residuals test

Standardized Residuals Tests:

			Statistic	p-Value
Jarque-Bera Test	R	Chi^2	0.546254	0.7609961
Shapiro-Wilk Test	R	W	0.984771	0.9059197
Ljung-Box Test	R	Q(10)	10.82257	0.3715076
Ljung-Box Test	R	Q(15)	14.44125	0.4923609
Ljung-Box Test	R	Q(20)	20.28814	0.44004
Ljung-Box Test	R^2	Q(10)	6.341955	0.7857622
Ljung-Box Test	R^2	Q(15)	11.33755	0.7283199
Ljung-Box Test	R^2	Q(20)	14.14789	0.8229191
LM Arch Test	R	TR^2	12.07839	0.4394045

4.12.1 **Volatility**

The volatility and residual plots on Fig 4 shows the volatility process for the past shock a_t, and it indicates that a large shock give rise to a large volatility, generating well- known behavior of volatility that is volatility clustering. The volatility plot indicates that volatility was high between August 2020 and February 2021 and this may be due to the economic staggering.

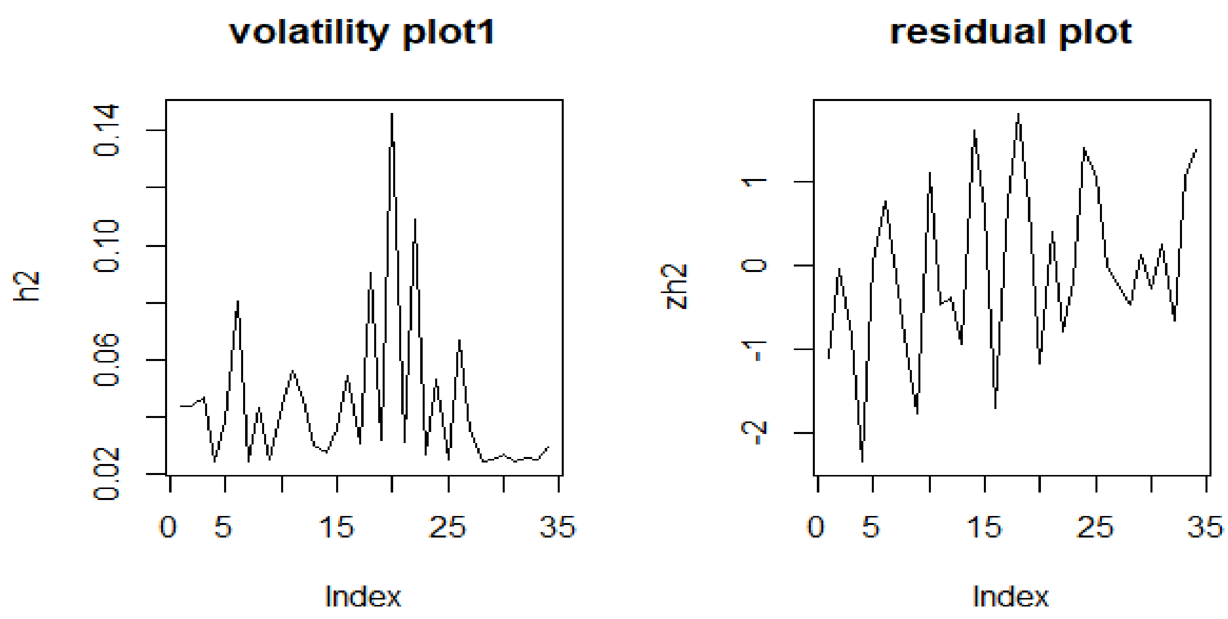

Figure 4 volatility process and residual plot

4.12.2 **Model interpretation and analysis**

The monthly-expected log return of Top 10 index is about 9.65%, which is quite remarkable, since the data obtained was for the transitional period. Investors can use Top 10 index to replicate their portfolio. The unconditional standard deviation of 0.204 and $\alpha_1^2 < \frac{1}{3}$ so that the unconditional fourth moment of index returns exist and we can use the model for analyzing the tail distribution of volatility in risk management. The unconditional variance (volatility) of the shock a_t is 0.04195.

4.12.3 **Forecasting**

The researcher also used the model to forecast for the volatility, for the next five months, the model indicates that volatility is going to be high. However, the ARCH model only describes how volatility changes over time, which means that it only captures volatility clustering. The model assumes that positive and negative stock have the same effect on volatility because it only depends on past square shocks; in practice, volatility tends to be asymmetric that is it reacts differently to positive and negative shocks. The ARCH model likely to over predict volatility because it response slowly to large shocks. Table 3 below shows the volatility and returns forecast of Top ten index based on the ARCH (2) Model. The model indicated that volatility would be high for the next five months, however the model does not indicates the cause of volatility, and it gives no indication of what causes such behavior to occur.

Table 4 volatility forecast for monthly returns of TOP 10 index

Horizon	1	2	3	4	5
Return	0.0945	0.0945	0.0945	0.0945	0.0945
Volatility	0.190	0.218	0.199	0.210	0.202

4.13 **AR (2)-GARCH (1, 1)**

The fitted joint estimates of AR (2)-GARCH (1, 1) gives;

$$r_t = 0.09048 + 0.1377r_{t-1} - 0.40207r_{t-2} + a_t$$

$$\sigma_t^2 = 0.1249 + 0.42638a_t^2 + 0.2120\sigma_t^2$$

The t ratio shows that all the estimated parameter are significant. The implied volatility (unconditional variance) from the volatility function at is

$$\frac{0.1249}{1-0.42638-0.2121} = 0.1874$$

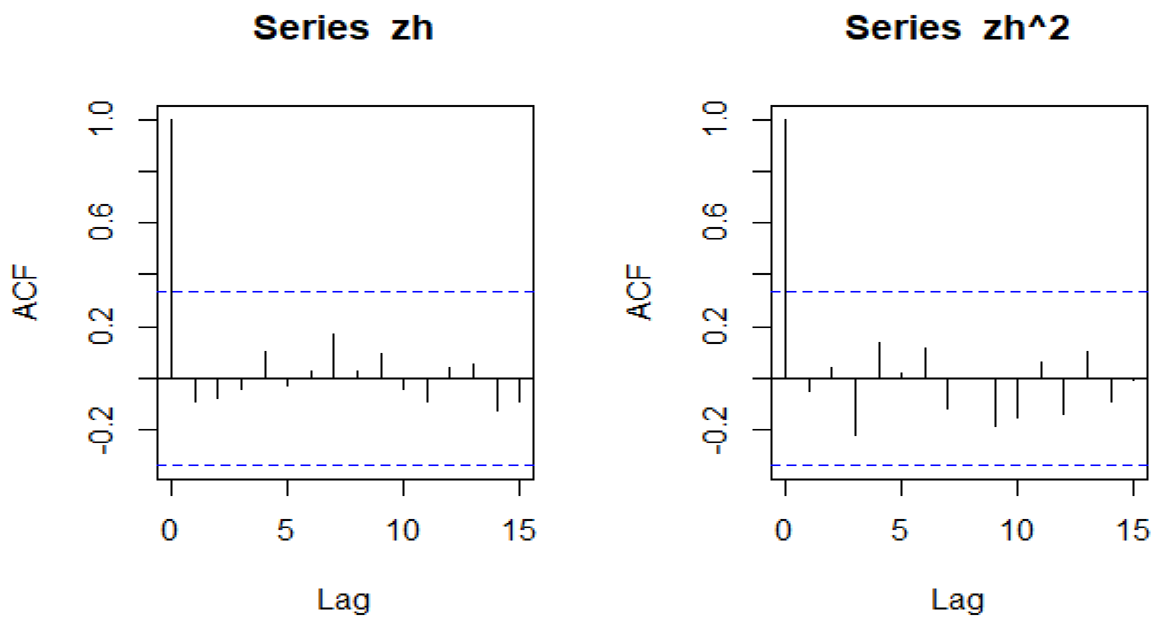

Figure 5 shows sample ACF of the standardized residuals and sample of squared standardized residuals

The sample ACF standardized residuals and squared standardized residuals fail to suggest any significance serial correlation or conditional heteroscedasticity. The Ljung-Box test statistics of standardized residuals a_t gives $Q(20) = 11.175$ and p value of 0.9416 and those of squared standardized residuals a_t^2 gives $Q(20) = 15.202$ and a p value of 0.765. Thus, the model seems adequate in describing the linear dependence between return and volatility series.

4.13.1 **Value at risk (VAR)**

According to Duffie and Pan (1997) and Jorion (2006), VAR is a single estimate of the amount by which an institution's position in a risk category could decline due to general market movements during a given period. Financial institutions and investors can use VAR to assess their risks or by a regulatory committee to set margin requirements for an investment. In addition, it ensures that the financial institutions can be still be in the business after a catastrophic event. $AR(2) - GARCH(1,1)$ was used to calculate the quartile conditional distribution(VAR of log returns).

The upper tail of the loss function is used to calculate VAR of a financial position. For a long financial position, loss occurs when the returns are negative. Therefore, the researcher used negative returns in analyzing data for a long financial position. The VAR calculated from the upper quantile of the distribution of returns r_{t-1} is given information available at time t is therefore in percentage. The dollar amount of VAR is then the cash value of the financial position times the volatility of the log return series. That is, VAR = Value × VAR (log returns).

Given the $AR(2) - GARCH(1,1)$ model, one-step ahead mean forecast $u_t(1) = -0.03776$ and one-step ahead volatility forecast $\sigma_t(1) = 0.02051$.

The 95% quantile for 21-day horizon (one month) under the normality assumption is then

$$VAR(of\ \log\ retuns) = u_t + 1.6449\sigma_t$$

$$= -0.03776 + 1.6449(0.02051)$$

$$= -0.00402$$

Let us consider a financial institution holding long position of $10 million with a tail probability of 0.05 then $VAR = 10000000 \times 0.00402 = \$40231.01$. The results shows that with probability 95%, the potential loss of holding that position for 21 days is 402310.01. However, in practical VAR may under estimate actual loss, if it occurs can be greater than VAR. To have a better potential loss one can consider the expected loss function to calculate the expected loss.

4.13.2 **Expected shortfall**

Given the 95% quartile the expected short fall is

$$E(S) = u_t + \frac{f(x_q)}{q}\sigma_t,\ f(x) = {}^{1}\!/_{\sqrt{2\pi}}\exp(-x^2/2)$$

$$= -0.03776 + 2.0627(0.02051)$$

$$= 0.00455$$

Considering the example of holding a long position of 10 million with a tail probability of 0.005 then $VAR = 10000000 \times 0.00455 = \$45000$. The results shows that with probability of 95%, the potential loss of holding that position for 21 days is $45000.

4.13.3 Asymmetric models TGARCH and EGARCH

The researcher used the exponential GARCH ($AR(2) - EGARCH(1,1)$ model to check for the applicability of asymmetric GARCH model to monthly returns of the index. The fitted model indicated that there is no leverage effect on index returns, because of a positive $Gamma(\gamma)$. The leverage effect indicator $\gamma = 0.962976$, a positive $gamma(\gamma)$ indicates that asymmetric models that is EGARCH and TGARCH could not be used to model volatility of Top 10 index.

4.14 Chapter summary

The findings indicates that symmetric GARCH models that is ARCH and GARCH model can be used to model volatility for Top 10 index on Zimbabwe Stock Exchange. The researcher derive an optimal model that can be used to forecast expected returns and volatility of ZSE market, portfolio construction and in risk management. The exponential GARCH model indicated that index returns on ZSE does not exhibit leverage effect. In fact, it disapprove the use of asymmetric GARCH models on ZSE.

4.15 ARCH (2) model output

```
Title:
 GARCH Modelling

Call:
 garchFit(formula = lm2 ~ garch(2, 0), data = lm2, trace = F)

Mean and Variance Equation:
 data ~ garch(2, 0)
<environment: 0x00000161813a8688>
 [data = lm2]

Conditional Distribution:
 norm

Coefficient(s):
        mu       omega      alpha1      alpha2
0.09453895  0.02446356  0.00000001  0.41574068

Std. Errors:
 based on Hessian

Error Analysis:
        Estimate  Std. Error  t value Pr(>|t|)
mu     9.454e-02   2.512e-02    3.763 0.000168 ***
omega  2.446e-02          NA       NA       NA
alpha1 1.000e-08          NA       NA       NA
alpha2 4.157e-01   2.340e-01    1.776 0.075672 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Log Likelihood:
 7.098506    normalized:  0.2087796


Standardised Residuals Tests:

                                Statistic p-Value

 Jarque-Bera Test   R    Chi^2  0.7675686 0.6812784

 Shapiro-Wilk Test  R    W      0.9743186 0.589846

 Ljung-Box Test     R    Q(10)  10.43572  0.403133

 Ljung-Box Test     R    Q(15)  15.40308  0.4227908

 Ljung-Box Test     R    Q(20)  22.20658  0.329407

 Ljung-Box Test     R^2  Q(10)  18.63473  0.04515506

 Ljung-Box Test     R^2  Q(15)  27.73198  0.02330824

 Ljung-Box Test     R^2  Q(20)  30.7599   0.05844104

 LM Arch Test       R    TR^2   12.22515  0.4277716


Information Criterion Statistics:

        AIC         BIC         SIC        HQIC

-0.04252543  0.13704640 -0.06651045  0.01871371
```

5. CHAPTER 5: SUMMARY, RECOMMENTATION AND CONCLUSION

5.1 Introduction

In the study, the researcher models the ZSE market volatility using conditional heteroscedasticity models. The derived GARCH (1,1) model was used to forecast expected return and volatility. the optimal function was used to estimate VAR for the market. This chapter gives the conclusion drawn from the study as well as recommendation on the performance of ZSE during the transition period.

5.2 Summary of findings and conclusion

The objective of the study was to find an optimal model for modelling volatility between symmetric and asymmetric GARCH model, forecasting of index return and volatility, and the estimate Value at Risk using Top 10 index monthly return data from November 2018 to October 2021. The economic instability during the period indicated by price and exchange rate fluctuations, increase in interest rates and high inflation rates affects the market volatility indicated by a period of high volatility.

The researcher derive the optimal GARCH(1,1) model and estimate the market risk, forecasting of the market return and volatility, and also estimation of VAR using derived optimal function. The forecasting indicated a period of low volatility exhibiting well-known volatility characteristic that is volatility clustering.

5.3 Limitations of the study

The main limitation of the study are mostly related to Empirical study approach particularly the use of the data set and methodology. The study only model volatility for a two-year period from November 2018 to October 2021 that is during the transitional period leading to a small sample taken. The study assumes that ZSE market is efficient; however, there may anomalies that causes the market to be inefficiency.

5.4 Suggestion for further research

According to the research finding it would be helpful to carry the study, using large sample data includes both data from multicurrency era and that of the RTGS and test the applicability of asymmetric GARCH type model to ZSE. The research needs more elaborate measure for example comparing the forecasting performance of the models using MSE (mean square error), Root Mean Square Error (RMSE) and absolute perfect error (MAPE) or using out sample data to compare the applicability of volatility models. The study only considered GARCH type volatility model other volatility model such as stochastic volatility models can be used in volatility modelling.

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7. APPENDIX 1

7.1 CODE A

```
####### importing data into R

read.table("ZSE-Top-10.txt",header=T)

m=read.table("ZSE-Top-10.txt",header=T)

dim(m)

price=m[,2]

###### calculating monthly Returns

m1=returns(price)

m2=na.omit(m1)

lm2=log(m2+1)

dim(lm2)

#### Distribution of returns

library(fBasics)

normalTest(lm2,method = c("jb"))

normalTest(lm2,method = c("sw"))

t.test(lm2)

plot(lm2,type="l",xlab="time",ylab="return")

####### stationary test

Box.test(lm2,lag = 12,type = c("Ljung"))

acf(lm2)

pacfPlot(lm2)

####### modeling index stock return.

####### symmetric garch modeling

####### arch test

library(nortsTest)

at=lm2-mean(lm2)

at^2

arch.test(at,arch = c("Lm"),alpha = 0.05,lag.max = 12)

arch.test(at,arch = c("box"),lag.max = 12)

##### order determination
```

```
acf(at^2)
pacf(at^2,lag.max = 12)
ord=ar(at^2,lag.max=12)
ord$aic
```

7.2 CODE B

```
####### arch model
library(fGarch)
mm2=garchFit(lm2~garch(2,0),data=lm2,trace=F)
summary(mm2)
predict(mm2,5)
###### analysis mm2@fit
z2=mm2@fit$series$z
h2=mm2@fit$series$h
x2=mm2@fit$series$x
volatility=sqrt(h2)
plot(h2,type="l",main="volatility plot1")
### standardized residuals for model checking
zh2=z2/sqrt(h2)
acf(zh2)
acf(zh2^2)
plot(zh2,type="l",main="residual plot")
#### residuals and volatility.
plot(z2^2,type="l")
lines(h2,col="red")
```

7.3 CODE C

```
######## garch(1,1) model
mm4=garchFit(lm2~garch(1,1),data = lm2,trace = F)
predict(mm4,5)
##### analysis mm4@fit
z3=mm4@fit$series$z
h3=mm4@fit$series$h
```

```
x4=mm4@fit$series$x
plot(h3,type="l",main="volatility plot")

##### ar(2)-garch(1,1)
mm5=garchFit(lm2~arma(2,0)+garch(1,1),data=lm2,trace=F)
p2=predict(mm5,2)
###### analysis mm5@fit
z=mm5@fit$series$z
h=mm5@fit$series$h
x=mm5@fit$series$x
plot(h,type="l",main="volatility plot")
# standardized residuals for model checking
zh=z/sqrt(h)
acf(zh)
acf(zh^2)
plot(zh^2,type="l")
```