OPEN ACCESS JOURNALS
Indiana Journal of Multidisciplinary Research
Abbriviate Tittle- Ind J Multi Res
ISSN *(Online)*- XXXX-XXXX
Journal Homepage Link- https://indianapublications.com/Journals/IJMR

INDIANA PUBLICATIONS
PRODUCTIVE AND QUALITY RESEARCH

Research Article

Volume-01|Issue-01|2021

Comparison of Arch Family Models Using E-Views Computer Software Packages: A Case of Zimbabwe Stock Exchange

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Article History
Received: 27.09.2021
Accepted: 13.11.2021
Published: 30.11.2021

Citation
Masimba, F., & Shadreck, M. (2021). Comparison of Arch Family Models Using E-Views Computer Software Packages: A Case of Zimbabwe Stock Exchange. *Indiana Journal of Multidisciplinary Research*, *1*(1), 1-10.

Abstract: An empirical analysis of the variance of Zimbabwe Stock Exchange (ZSE) Industrial index was performed using various GARCH models. E-views computer software packages were employed in comparing the performance of GARCH models. The data set consisted of daily closing prices. The selected time span of the data is from 2009 to 2014. The performance of ARCH, GARCH, EGARCH AND TARCH models was compared using the AIC and SIC. Augmented Dickey Fuller stationarity test were performed and return series was found to be stationary at level. The ARCH-LM test was conducted to detect whether ARCH effects existed in our series and it proved the existence of ARCH effects, justifying application of ARCH family models. The application of AIC and SIC showed that the best model was ARCH (5), the second being TGARCH, followed by GARCH (1.1) and the last was EGARCH. Diagnostic test were performed on the best model, ARCH 5 and it was found that serial correlation did not exists in residuals using the correlogram of squared residuals. What was unfavourable was the lack of normality in residuals using the Jaque-bera tests. The study recommends use of ARCH (5) when forecasting volatility in the Zimbabwe Stock Exchange.

Keywords: Volatility, ZSE, ARCH, GARCH, EGARCH and TGARCH.

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INTRODUCTION

The main aim of investing is to reap good future rewards. Any rational investor invests because he at least expects to regain his money back plus at least a positive return. The chances of gaining or losing are contained in volatility measures.

Returns are generally considered to be random variables. An asset's volatility then describes the spread of outcomes of this variable (return). Volatility is a very important factor in numerous financial applications in which its role is to estimate the value of market risk. It is also a key parameter in the pricing process of financial derivatives. Modern option-pricing techniques use a volatility parameter for price evaluation. In addition, volatility is also important in risk management applications and is used in general portfolio management.

Thus, it is very crucial for financial agents to know the current value of the volatility of their assets, as well as to estimate their future values (Brooks, 2008)

The prediction of volatility is a difficult task even for financial experts in the field. Econometric Models can provide financial institutions with a valuable estimate of a future market trend. Although some experts believe that future events are totally unpredictable, existing evidence prove contrary. The fact that financial volatility has a tendency to cluster and depict significant autocorrelation, justify the need for formalizing the concept of volatility and creating volatility-forecasting mathematical techniques. Since the late 1970s, many models have been introduced.

Although there are many models that can be used to forecast stock returns, the ZSE currently does not have a model that forecast the stock price.

Problem Statement

Volatility is not constant and it demonstrates clustering behavior and this leads to the need for continuous study. The Zimbabwean economy is characterized by different eras with different economic reforms and with clustering effects; the consequences of different reforms may persist for some time. Since volatility plays a very crucial role in option pricing, the data must be kept current and accurate. Very few papers have compared ARCH family models using AIC and SIC to choose the best performing models in emerging markets and in particular, according to the knowledge of the researcher, no papers have compared ARCH family models for the period 2009 to 2015 for the Zimbabwean market in the dollarization period. Thus the need to find the best model since Zimbabwe does not have a model that forecast stock prices and volatility. The study will come up with a best model to forecast volatility since the Zimbabwe Stock Exchange currently does not have a model that forecast stock prices and volatility.

Research objectives

The purpose of this study is to compare the performance of five models for predicting volatility in the Zimbabwe stock market. The objective of the paper is to investigate:

- Whether the Zimbabwean stock market volatility be modeled by ARCH approaches.
- The ARCH process which is appropriate for modeling the volatility of Zimbabwean stock market.

Research questions

In order to achieve the above objectives, the study will try to answer the following research questions:

- Can the Zimbabwean stock market volatility be modeled by ARCH approaches, namely, ARCH, GARCH, EGARCH and TGARCH during the dollarization era?
- Which GARCH process is appropriate for modeling the volatility of Zimbabwean stock market during the dollarization era?

LITERATURE REVIEW

Theoretical Review

In finance, people have interest in the outcomes of asset returns. Volatility describes the spread of all outcomes of an uncertain variable (Ladokhin, 2009). It can be viewed as a quantified measure of market risk. Volatility is closely related to risk, but it is not exactly the same. Risk is the possibility of more than one outcome of some event (e.g. stock returns) whereas volatility measures a spread of outcome, both positive and negative outcomes.

In literature, there are several characteristics which are very important to note for the purposes of modeling and forecasting (Brooks, 2008). Some of these characteristics include the following:

- *Fat tails.* Market returns exhibits distributions with fatter tails than the normal distribution, resulting in a higher kurtosis.
- *Volatility Clustering.* Volatility is usually not constant over time and exhibits certain patterns. Usually periods of high volatility are followed by prolonged periods of high volatility and periods of low volatility are usually followed by prolonged periods of low volatility. As a result, the economy has cycles with high volatility and low volatility periods.
- *Leverage effect.* According to Brooks (2008) price movements are negatively correlated with
- *Co-movements in volatility.* Ladokhin (2009) identified that volatility of different markets tends to move in certain patterns. Meaning that a high volatility of one financial asset will most likely cause higher volatility of the other asset.

Volatility modelling can be grouped into 4 categories, namely, historic volatility models, implied volatility models, Neural Network and Autoregressive and Heteroskedastic models.

Examples of Historical volatility models are Historical average, Simple moving average, Exponential smoothing and Exponential weighted moving average. The advantages include easy to use, relatively good results (except historical average) and the main disadvantage is that after sudden price movements these models tend to significantly over estimate the volatility.

Implied volatilities are the volatilities implied by the market prices of the options Ladokhin (2009). Unfortunately there is no direct formula for computing the implied volatility. Advantages: Good results, these models are based on strong theoretical results. Disadvantages: complex to implement; not suitable for all products (only for that, which are an underlying for an actively trading options); are dependent on sometimes irrational expectations of investors.

Autoregressive and Heteroskedastic models model was first introduced by Engle in 1982 (Engle, 1982). ARCH model and its extensions and denominations (GARCH, EGARCH, etc.) are among the most popular models for forecasting market returns and volatility. Advantages: an existence of a big number of theoretical researches of these models. Disadvantages: moderate forecasting accuracy; complex to implement and optimize (Ladokhin, 2009)

Models based on Neural Networks Artificial Neural Networks (or Neural Networks) are popular statistic techniques for machine learning. Originally, they were created as an attempt to model the biological neuron system. This attempt was made to create a new approach to the computing, and to possible mimic the behavior of a human brain. This field of a science was created in the late 1950s, and was extensively developed in the 1980s. Some definitions have to be given, before introducing the volatility model based on the Neural Networks. Advantages: relatively good results; an ability to build models which use not only historical returns as an input, but also other related financial time series and variables. Disadvantages: complex to implement and to find suitable architecture; can forecast only dependencies from a previous observations (Ladokhin, 2009)

The choice of the best form of model is a hot issue in the field of financial econometrics. Samouilhan & Shannon (2008) reviewed 39 papers discussing the merits of each of the two categories, found that half

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were in favor of implied volatility modelling and the other half viewed the historic models as being superior.

An interesting paper by Venter (2003) showed that implied volatility modelling for JSE warrants compared marginally better than historic models. In his paper, Venter comes to the conclusion that no model can be used as a ‘cookie cutter’. In other words, no matter what category of volatility modelling is used, it must be fit for purpose. This argument by Venter, is challenged by Hansen *et al.* (2005) where they asked the question whether or not anything beats a GARCH (1,1) model. They found no evidence that a GARCH (1,1) model is outperformed by other complex and sophisticated models when analyzing exchange rates. However they did concede that the GARCH (1,1) is inferior when analyzing IBM stock returns.

Empirical Review

Heteroskedasticity (changing variance) can be modelled by Autoregressive conditional heteroskedasticity (ARCH) family models. Many studies support the GARCH type models as best for forecasting stock market volatility (Alberg *et al.*, 2008; & Hien 2008). Also in literature many researchers have used GARCH family models.

Makhwiting *et al.* (2012) used GARCH type models for modelling daily returns on the Johannesburg Stock Exchange. Their results indicate that the daily returns can be characterized by the GARCH type models. Their out of sample forecasting evaluations indicate that the ARMA (0, 1)-GARCH (1,1) model achieve the most accurate volatility forecasts.

Song (2014) conducted a full simulation exercise whereby the returns of several JSE indices were tested and modelled using a variety of GARCH models. The Model Confidence Set was then used to trim the total group of models down to subset which represented the models that were equally good. The EGARCH family of models was proven to be the most consistently chosen by the MCS as the superior model. The Mean Squared Error model evaluation revealed that for time horizons greater than 10 days, the MCS performed better than the GARCH (1,1) model. The GARCH (1,1) had superior 5-day-ahead forecasting power foremost of the indices.

Abdalla *et al.* (2012) modelled and estimated stock return volatility in two African markets; the Sudanese stock market (Khartoum Stock Exchange, KSE), and the Egyptian stock market (Cairo and Alexandria Stock Exchange, CASE) by applying different univariate specifications of GARCH type models for daily observations on the index series of each market over the period of 2nd January 2006 to 30th November 2010, as well as describing special features of the markets in terms of trading activity and index components and calculations. A total of five different models were considered in this paper. These models are GARCH(1,1), GARCH-M(1,1), exponential GARCH(1,1), threshold GARCH(1,1) and power GARCH(1,1). First, the paper found strong evidence that daily returns could be characterized by the above mentioned models for the two markets, KSE and CASE data showed a significant departure from normality and the existence of heteroscedasticity in the residuals series. Second, the parameter estimates of the GARCH (1,1) models indicate that the conditional volatility of stock returns on the Khartoum Stock Exchange is an explosive process, while it is quite persistent for the CASE index returns series. Third, the parameter describing the conditional variance in the mean equation, measuring the risk premium effect for GARCH-M (1,1), is statistically significant in the two markets, and the sign of the risk premium parameter is positive. The implication is that an increase in volatility is linked to an increase of returns, which is an expected result. Fourth, based on asymmetrical EGARCH (1,1) and TGARCH(1,1) estimation, the results show a significant evidence for the existence of the leverage effects in the two markets, the same result is confirmed only for the CASE by using the PGARCH(1,1) model.

Babikir *et al.* (2012) modelled volatility and investigated the empirical relevance of structural breaks in accurately forecasting the volatility of stock returns in South Africa using in on the JSE All share index from 1995 to 2010. Results from modified ICSS algorithm identify two structural breaks in the unconditional volatility of the stock market return series in South Africa. These occurred in March and October 2009 attributable to the impact of the global financial crisis and began to be felt on the South African economy. The fitted full sample GARCH (1, 1) model and the sub persistence with $\alpha + \beta$ ranging between 0.952 to 0.995 indicating that stock market returns in South Africa is characterized by conditional heteroscedasticity. This confirms that structural breaks are a relevant feature of stock market return volatility in South Africa and there to be accounted for to enhance accuracy in volatility forecasts of stock market returns in South Africa. For shorter time horizons the MS GARCH (1,1) model performed better, while the GJR-GARCH was better suited to longer horizons, but in general, the asymmetric models fail to outperform the GARCH (1,1) model.

Mutendadzamera & Mutasa (2014) investigated whether the stock prices on the ZSE can be predicted using ARIMA and ARCH/GARCH models. The study attempted to explore econometrics models to predict future stock prices on the Zimbabwe Stock Exchange (ZSE) selected counters. The final models are found to be Econet Wireless, ARIMA(1,1,0), Dairiboard, ARIMA(1,1,0), Delta, ARIMA(1,1,1), Seed Co, ARIMA(1,1,1) and Old Mutual, ARIMA(1,1,0). The GARCH(1,1 model for all the counters forecast better than ARIMA models considering the minimum deviations of the forecasted values from the actual ones. They concluded that GARCH (1, 1) model outperforms ARIMA models in modeling stock prices in their study.

RESEARCH METHODOLOGY AND DATA

E-views were employed in running regressions. The main methodologies that are used in modeling stock market volatility are the Autoregressive conditional heteroscedasticity (ARCH) and its generalization (GARCH) models. In this paper ARCH and different univariate GARCH specifications are used to model stock returns volatility in the Zimbabwe stock exchange and a comparison is made to find the best model among them.

There are two different equations for all these models: the first one for the conditional mean and the second one for the conditional variance. Autocorrelation Function and Partial Autocorrelation Function were observed in order to choose the mean equation. In economic theory, if there is a geometrically decaying ACF it is advisable to use autoregressive model. The order is seen through the number of non-zero points of PACF and the best model is the one that minimizes the AIC and SIC. In this paper the focus is on the variance equation as it provides estimates and conditional forecast of volatility.

The selected time span of the data is from 2009 to 2014. The returns were calculated using $r_t = \log(P_t) - \log(P_{t-1})$ from closing prices of the Zimbabwe Stock Exchange Industrial Index.

ARCH Model

ARCH models based on the variance of the error term at time t depends on the realized values of the squared error terms in previous time periods. The model can be represented as:

$$\mathrm{y_t = u_t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

$$u_t \sim N\left(0, \delta^2{}_t\right)$$

$$\delta^2{}_t = \omega + \sum_{t=1}^{q} \alpha_j u_{t-i}^2 \ldots\ldots\ldots\ldots\ldots\ldots..(2)$$

This model is referred to as ARCH(q), where q refers to the order of the lagged squared returns included in the model. If we use ARCH(1) model it becomes

$$\delta^2{}_t = \omega + \alpha_1 u_{t-1}^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(3)$$

Since $\delta^2{}_t$ is a conditional variance, its value must always be strictly positive; a negative variance at any point in time would be meaningless. To have positive conditional variance estimates, all of the coefficients in the conditional variance are usually required to be non-negative. Thus coefficients must be satisfy $\omega \succ 0$ and . $\alpha_1 \geq 0$.

The Model takes into account crucial characteristic in financial time series data, like fat tails. The main disadvantage of the ARCH Model is that it does not take into account leverage effects.

GARCH Model

The GARCH (p,q) model developed Bollerslev (1986); Taylor (1986) developed allows the conditional variance of variable to be dependent upon previous lags of the squared residual from the mean equation and present news about the volatility from the previous period. It can be represented as:

$$\delta^2{}_t = \omega + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{i=1}^{p} \beta_i \delta^2{}_{t-i} \ldots\ldots\ldots\ldots\ldots\ldots(4)$$

For a simple model GARCH (1,1) process, the conditional variance can be represented as:

$$\delta^2{}_t = \omega + \alpha_1 u_{t-1}^2 + \beta_1 \delta^2{}_{t-1} \ldots\ldots\ldots\ldots\ldots..(5)$$

Under the hypothesis of covariance stationarity, the unconditional variance $\delta^2{}_t$ can be found by taking the unconditional expectation of equation 5.

We find that

$$\delta^2 = \omega + \alpha_1 \delta^2 + \beta_1 \delta^2 \ldots\ldots\ldots\ldots\ldots\ldots(6)$$

Solving the equation 5 we have

$$\delta^2 = \frac{\omega}{1 - \alpha_1 - \beta_1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (7)$$

For this unconditional variance to exist, it must be the case that $\alpha_1 + \beta_1 < 1$ and for it to be positive, we require that $\omega > 0$.

The main advantage of GARCH over ARCH Model is that it allows past variances to influence the current variance. The disadvantages include being ssymmetric to both positive and negative prior returns, restrictive on β and α and otherwise we will have an infinite fourth moment, provides no explanation as to what causes the variation in volatility, not sufficiently adaptive in prediction – because they react slowly to large isolated shocks and tail behaviour of GARCH models remains too short even with a standardized student-t innovations.

Threshold GARCH

The TGARCH model is a simple extension of GARCH with an additional term added to account for possible asymmetries (Brooks, 2008). Zakoian (1994); & Glostern *et al.* (1993) developed the GARCH model

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which allows the conditional variance has a different response to past negative and positive innovations.

$$\delta^2{}_t = \omega + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \gamma_i u_{t-i}^2 d_{t-1} + \sum_{i=1}^{p} \beta_j \delta_{t-j}^2 \quad \text{……..(8)}$$

Where d_{t-1} is a dummy variable that is:

$$d_{t-1} = \begin{cases} 1 \; if \;\; u_{t-1} < 0, & bad \; news \\ 0 \; if \;\; u_{t-1} \geq 0, & good \; news \end{cases}$$

In the model, effect of good news shows their impact by α_i, while bad news shows their impact by $\alpha + \gamma$. In addition if $\gamma \neq 0$ news impact is asymmetric and $\gamma > 0$ leverage effect exists. To satisfy non-negativity condition coefficients would be $\alpha_0 > 0$, $\alpha_i > 0$, $\beta \geq 0$ and $\alpha_i + \gamma_i \geq 0$. That is the model is still acceptable, even if $\gamma_i < 0$, provided that $\alpha_i + \gamma_i \geq 0$ (Brooks, 2008).

Exponential GARCH

Exponential GARCH (EGARCH) proposed by Nelson (1991) which has form of leverage effects in its equation. In the EGARCH model the specification for the conditional covariance is given by the following form:

$$\log(\delta^2{}_t) = \omega + \sum_{j=1}^{q} \beta_j \log(\delta_{t-j}^2) + \sum_{i=1}^{p} \alpha_i \left| \frac{u_{t=i}}{\sqrt{\delta^2{}_{t=i}}} \right| + \sum_{k=1}^{r} \gamma_k \frac{u_{t-k}}{\sqrt{\delta^2{}_{t-k}}} \quad \text{……..(9)}$$

According to Brooks (2008), there are advantages over pure GARCH specification; by using $\log(\delta^2{}_t)$ even if the parameters are negative, will be positive and asymmetries are allowed for under the EGARCH formulation.

In the equation γ_k represent leverage effects which accounts for the asymmetry of the model. While the basic GARCH model requires the restrictions the EGARCH model allows unrestricted estimation of the variance.

If $\gamma_k < 0$ it indicates leverage effect exist and if $\gamma_k \neq 0$ impact is asymmetric.

Diagnostic Tests

According to Gujarati (2004) diagnostic tests should be performed so that the model finally chosen is a good model in the sense that all the estimated coefficients have the right signs, they are statistically significant on the basis of the *t* and *F* tests, and the R-Squared value is reasonably high. In this regard, this study shall employ Stationarity test, the Histogram and Normality test, and the Ramsey test, and Serial Correlation LM test.

Stationarity Tests

According to Dickey & Fuller (1981), a stationary series can be defined as one with a constant mean, constant variance and a constant auto-covariance. It is very important to test for non-stationarity mainly for the following reasons: stationarity or otherwise of a series can influence its behavior and properties, for example, persistence of shocks will be finite for a stationary series and infinite for non-stationary series, two variables trending over time may produce a high R^2 if a regression of one on the other is run even if the two are totally unrelated, and if the variables in the regression model are not stationary, then it can be proved that the standard assumptions for asymptotic analysis will not hold and the usual “t-ratios” will not follow a t-distribution, so one cannot validly undertake hypothesis tests about the regression parameters.

Augmented Dick-Fuller Tests (ADF) Tests are used to find out if the series are stationary. These tests are based on the following regression form with constant and trend

$\Delta Y_t = \alpha + \delta Y_{t-1} + \mu_t$………1 intercept only

$\Delta Y_t = \alpha + \beta T + \delta Y_{t-1} + \mu_t$….2 trend and intercept

$\Delta Y_t = \delta Y_{t-1} + \mu_t$ …………3 no trend no intercept

Decision rule

If t* > ADF critical value, unit root exists and we accept the null hypothesis.

If t* < ADF critical value, unit root does not exist and we reject the null hypothesis.

Testing for ARCH effects (Heteroscedasticity Test)

Before estimating a GARCH model it is of paramount importance to first check if there are ARCH effects (heteterosceasticity) in the residuals of the model. This is done by the ARCH test of heteroscedasticity. Engel (1982) proposed a LM test for ARCH.The test is based on the regression of squared residuals on lagged, squared residuals. The statistic is distributed as and provides a test of the hypothesis that the coefficients of the lagged squared residuals are all zero – that is no ARCH. The statistic is the outcome of the Langrange Multiplier (LM) test and has an asymptotic distribution with degrees of freedom equal to the number of lagged squared residuals.

Normality Test

Jarque Bera (JB) test of normality is employed. The JB test of normality is an asymptotic, or it is a test of goodness to fit to normal distribution for a large sample size, test. It is also based on the OLS residuals and uses the chi-square distribution with 2 degree of freedom. (Gugarati, 2004)

H0: The error terms are normally distributed.

H1: The error terms are not normally distributed.

Residual Diagnostics/Correlogram-Q-statistics

A test whether a volatility model has adequately captured all of the persistence in the variance of returns is to look at the correlogram of the standardized squared residuals. If the model is adequate then the standardized squared residuals should be serial uncorrelated. If there is no serial correlation in the residuals, the autocorrelations and partial autocorrelations at all lags should be nearly zero, and all *Q*-statistics should be insignificant with large *p*-values.

RESULTS AND FINDINGS

Choice of Mean Equation

Table 1: Autocorrelation Function/Partial Autocorrelation Function

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.455	0.455	304.48	0.000
		2	0.297	0.113	434.01	0.000
		3	0.181	0.013	482.36	0.000
		4	0.049	-0.078	485.95	0.000
		5	0.014	-0.005	486.26	0.000

In economic theory, if there is a geometrically decaying ACF it is advisable to use autoregressive model. The order is seen through the number of non-zero points of PACF. By Looking at the table, it can be seen that at lag 1and lag 2, there are non-zero PACF.

Table 2: Aikaike Information Criterion (AIC) and Schwarz Information Criterion (SIC)

	AIC	**SIC**
AR(1)	-5.896274	-5.892667
AR(2)	-5.786850	-5.783241

The best model is the one that minimizes the AIC and SIC. Since the AR (1) Model minimizes both the AIC and SIC, the AR (1) Model is used in this study as the mean equation.

Descriptive statistics

Table 3: Descriptive Statistics

Variable	**R**
Mean	0.000339
Median	-0.000104
Maximum	0.094371
Minimum	-0.190372
Std Deviation	0.014238
Skewness	-2.214550
Kurtosis	39.14970
Jarque-Bera	81132.56
Probability	0.000000

According to Emenike (2010) in a normally distributed series, skewness is 0 and kurtosis is 3. The coefficient of skewness measures asymmetry. A positive skew indicates that the tail on the right side is longer than the left side and the bulk of the values lie to the left of the mean. In this case, skewness is -2.214550, confirming asymmetry and a tail on the left side. This also means that the average magnitude of positive deviations is smaller than the average magnitude of negative deviations.

The coefficient of kurtosis measures the peakedness of distribution. The value for kurtosis is 39.14970 and since it is greater than 3, this suggests that there is peakedness in the return, r .The Jarque-Bera statistic is significant at 5% level, and this indicates much higher distributions than the normal distribution. From this it can be observed that the R variable exhibits significant deviations from normality. This demonstrates significant leptokurtosis.

Also Emenike (2010) observed that the Nigerian Stock return series do not conform to normal distribution but display negative skewness and leptokurtic distribution.

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Stationarity

To determine the characteristics of the variable, stationarity tests were carried out using the ADF tests. The unit root test results of the two variables are summarized in the table below.

Table 4: Unit Root Test at Level

Variable	Intercept Only			Trend And Intercept			No Trend, No Intercept		
	ADF Statistic	Critical value 5%	Inference	ADF Statistic	Critical value 5%	Inference	ADF Statistic	Critical value 5%	Inference
R	-19.52010	-2.8640	I(0)	-19.71353	-2.8640	I(0)	-19.44457	-1.9396	I(0)

Table 4 gives the summary of unit root test results and for detailed results refers to Appendix.

As shown in table 4, the variable, risstationary (it does not contain a unit root) as indicated by the fact that its critical value is all larger (in absolute terms) than the calculated ADF statistic and hence we do reject the null hypothesis: that the time series data variable is non-stationary.

ARCH-LM Test

According Brooks (2008), it is important first to compute the Engel (1982) test for ARCH before estimating a GARCH-type model to make sure that this class of models is appropriate for the data. In this study, the ARCH-LM test was used to test for ARCH effects on the residuals. The results are presented by table 5 below.

Table 5: Arch- LM Test

	ARCH-LM TEST
ARCH LM test statistic(obs R-Squared)	221.9349
Prob. (chi-square)	0.000000

Note: *H*0: There are no ARCH effects in the residual series.

P=0.00000 which is less than 5% so we reject null hypothesis and accept the alternative hypothesis. The Alternative hypothesis: there are ARCH effects in the residuals. The zero probability value strongly shows the presence of heteroscedasticity in the residuals and this justifies the use of ARCH family models in this study. EGARCH is part of the ARCH family models. The test can also be complemented by the correlogram of squared residuals.

Table 6: Correlogram of Squared Residuals

	AC	PAC	Q-Stat	Prob
1	0.379	0.379	210.83	0.000
2	0.229	0.100	287.85	0.000
3	0.236	0.141	369.66	0.000
4	0.231	0.107	448.41	0.000
5	0.198	0.061	506.08	0.000
6	0.278	0.172	620.01	0.000
7	0.229	0.046	697.66	0.000
8	0.365	0.256	894.01	0.000
9	0.162	-0.124	932.76	0.000
10	0.146	0.023	964.22	0.000
11	0.267	0.148	1069.5	0.000
12	0.226	0.001	1145.0	0.000
13	0.064	-0.126	1151.0	0.000
14	0.046	-0.134	1154.1	0.000
15	0.103	0.048	1170.0	0.000

Table 6 presence evidence of ARCH effects as judged by the autocorrelations of the squared residuals. The test p-values are all significant, and leads to the rejection of the no ARCH hypothesis. According Meyer (2011) autocorrelation of squared residuals or absolute returns suggest the presence of strong dependencies in higher moments, something that in turn is indicative of conditional heteroscedasticity. Autocorrelation has been observed; as a result we conclude presence of heteroscedasticity in the residuals. Presence of heteroscedasticity in residuals points to the need for the GARCH family model.

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Empirical Results

Table 7: Estimation results of different ARCH models for Zimbabwe Stock Exchange

Coefficients	**ARCH(1)**	**ARCH(2)**	**ARCH(3)**	**ARCH(5)**	**GARCH(1,1)**	**TGARCH(1,1)**	**EGARCH(1,1)**
Mean equation							
μ	0.571052	0.397542	0.44414	0.474004	0.432584	0.433001	0.458267
Variance							
ω	3.63E-05*	2.99E-05*	2.53E-05*	2.24E-05*	1.03E-05*	1.05E-05*	-2.5899477*
α	1.129464*	0.893136*	0.861526*	0.504807*	0.499216*	0.381453*	0.868286*
		0.194357*	0.110874	0.093903*			
			0.122680*	0.027729*			
				0.042986*			
				0.279786*			
β					0.507650*	0.487609*	0.791590*
γ						0.318375*	-0.146127*
α + β					1.006866	0.869062	1.659876
Log likihood	4838.552	4885.826	4922.994	4952.056	4931.986	4940.296	4910.511
AIC and SIC							
AIC	-6.59244	-6.65552	-6.70483	-6.74173	-6.71845	-6.72842	-6.68781
SIC	-6.58162	-6.6411	-6.6868	-6.71648	-6.70403	-6.71039	-6.66978

Notes: * denotes significance at 5% level

In the results for the variance equation in Table 7 above, the two types of coefficients in ARCH model are all significant, the constant and the ARCH term. The lagged squared disturbances have an effect on conditional variance.

For the GARCH (1,1), the three coefficients, namely, the constant, ARCH term and GARCH term are statistically significant, indicating that, lagged conditional variance and lagged squared disturbance have an impact on the conditional variance. The persistence coefficients (the sum of the two estimated ARCH and GARCH coefficients) in the GARCH(1,1) model for the Zimbabwe Stock Exchange is very close to one which is required to have a mean reverting variance process, indicating that volatility shocks are quite persistent, but not explosive. Unlike the TGARCH which also show volatility persistence which is not explosive, the EGARCH show one which is explosive.

The other two models, EGARCH (1,1) and TGARCH (1,1) are asymmetric models. The main distinction between lies in the fact that in the EGARCH model there is no need of non-negative restriction of the parameters but in the TGARCH model parameters must satisfy the positive condition. The main advantage of these two models is that they capture leverage effects. The asymmetric (leverage) effect in the EGARCH Model in Table 1 statistically significant with negative sign, indicating that negative shocks imply a higher next period conditional variance than positive shocks of the same sign, which indicates the existence of leverage effects in the returns of the Zimbabwe stock market index. Also in the TGARCH, the coefficient for the leverage effect is significant and positive. The significance of this coefficient shows that negative shocks (bad news) have a larger effect on the conditional variance (volatility) than positive shocks (good news) of the same magnitude.

In comparing the models the AIC and SIC can be employed. The rule here is the lower the AIC or SIC the better the model. The application of AIC and SIC showed that the best model is ARCH (5), the second being TGARCH, followed by GARCH (1.1) and the last was EGARCH.

DIAGNOSTIC CHECKING OF THE BEST MODEL (ARCH 5)

ARCH LM Test

Table 8: ARCH-LM Test

	ARCH-LM TEST
ARCH LM test statistic(obs R-Squared)	0.036594
Prob. (chi-square)	0.848294

Note: *H*0: There are no ARCH effects in the residual series.

The Table 8 presents results for the ARCH-LM test. The p value of the Obs*R-squared (0.848294) is not significant; it is greater than 0.05 and this indicates that there is no ARCH effects present. This shows that there is no heteroscedasticity in the residuals. This provides strong evidence that the GARCH can eliminate the problem of heteroscedasticity. Initially, with OLS, there was the presence of ARCH in the residuals. This made the use of the ARCH family model appropriate and with the use of the GARCH technique; the ARCH effects in the residuals were removed.

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Serial correlation

Table 9. Correlogram Squared Residuals

	AC	PAC	Q-Stat	Prob
1	-0.005	-0.005	0.0367	0.848
2	-0.016	-0.016	0.4059	0.816
3	-0.008	-0.008	0.4967	0.920
4	0.005	0.005	0.5356	0.970
5	-0.025	-0.025	1.4584	0.918
6	-0.005	-0.005	1.4994	0.960
7	-0.003	-0.003	1.5097	0.982
8	-0.008	-0.008	1.6005	0.991
9	0.006	0.006	1.6571	0.996
10	0.015	0.014	1.9811	0.996
11	0.000	0.000	1.9811	0.999
12	0.003	0.004	1.9949	0.999
13	0.003	0.003	2.0095	1.000
14	0.002	0.002	2.0130	1.000
15	0.008	0.009	2.1146	1.000

Table 9 shows that the *Q*-statistics are all significant at all lags under the ARCH (5) model, indicating that there is no significant serial correlation in the residuals. All p-values are above 0.05 and as a result of this the null hypothesis of no serial correlation is not rejected. Thus the model was good.

Normality test

In economic theory, residuals are expected to be normally distributed. The table below shows the results of the normality test:

Table 10: Normality Test Results

	ARCH (5)
Skewness	-0.645617
Kurtosis	14.70772
JB	8480.366
(Probability)	0.0000

Table 10 presents results from the Normality test. Results show that the unfavourable thing is that our residuals are not normal. Many economists believe that it does not matter even if residuals are not normal. Our model has the advantages of no ARCH effects in the residuals and no serial correlation in the residuals.

POLICY RECOMMENDATIONS AND CONCLUSIONS

An analysis of the variance of Zimbabwe Stock Exchange (ZSE) Industrial index was performed using various GARCH models. The data set consisted of daily closing prices. The selected time span of the data is from 2009 to 2014. The returns were calculated using $r_t = \log(P_t) - \log(P_{t-1})$. The performance of ARCH, GARCH, EGARCH AND TARCH models was compared using the AIC and SIC. Augmented dick Fuller stationarity test were performed and rt was found to be stationary at level. The ARCH-LM test was conducted to detect whether ARCH effects existed in our series and it proved the existence of ARCH effects, justifying application of ARCH family models. The application of AIC and SIC showed that the best model was ARCH (5), the second -being TGARCH, followed by GARCH (1.1) and the last was EGARCH. Diagnostic test were performed on the best model, ARCH 5 and it was found that serial correlation did not exists in residuals using the correlogram of squared residuals and no ARCH effect were found in the residuals supporting the notion that ARCH family models eliminate ARCH effects. What was unfavourable was the lack of normality in residuals using the Jacbeira tests. However, the normality test showed that the residuals were not normally distributed. Various studies in the past have also faced a similar scenario. The study recommends use of ARCH (5) when forecasting volatility in the Zimbabwe Stock Exchange.

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