Stock Market Volatility Analysis using GARCH Family Models: Evidence from Zimbabwe Stock Exchange

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Abstract:- *Understanding the pattern of stock market volatility is important to investors as well as for investment policy. Volatility is directly associated with risks and returns, higher the volatility the more financial market is unstable. The volatility of the Zimbabwean stock market is modeled using monthly return series consisting of 109 observations from January 2010 to January 2019. ARCH effects test confirmed the use of GARCH family models. Symmetric and asymmetric models were used namely: GARCH(1,1), GARCH-M(1,1), IGARCH(1,1) and EGARCH(1,1). Post-estimation test for further ARCH effects were done for each model to confirm its efficiency for policy. EGARCH(1,1) turned to be the best model using both the AIC and SIC criterions; with the presence of asymmetry found to be significant. The study concludes that positive and negative shocks have different effects on the stock market returns series. Bad and good news will increase volatility of stock market returns in different magnitude. This simply imply that investors on the Zimbabwean stock exchange react differently to information depending be it positive or negative in making investment decisions.*
Key words*: Stock Market, Volatility, ARCH, GARCH, IGARCH, GARCH-M, EGARCH, Risk Premium, Zimbabwe*
JEL Codes*: C22, C58, D81, D82, E22, E44, E47, G02, G14, G15, N27, O16, R53*

1. Introduction

The stock market is a large financial entity that serves many purposes, and allows the public to engage in corporate activity which can suit both investors and companies alike (Bonga, 2014). Volatility refers to the amount of uncertainty or risk about the size of changes in a security's value (Banumathy and Azhagaiah, 2015). Supported also by Koima, Mwita and Nassiuma (2015), volatility may also be described as the rate and magnitude of price changes which is referred to as a risk in finance.

Volatility is a measure of dispersion around the mean or average return of a security, and one way to measure volatility is by using the standard deviation or variance. Proper understanding and modeling of volatility are of practical importance in the financial industry in relation to for example risk management, portfolio allocation and pricing of financial instruments (Jakobsen, 2018). Many economic models assume that the variance, as a measure of uncertainty, is constant through time; however, empirical evidence rejects this assumption (Surya, 2008). Engle (1982), indicated that economic time series have been found to exhibit periods of unusually large volatility followed by periods of relative tranquility. As supported by Banumathy and Azhagaiah, (2015), the time series are found to depend on their own past value (autoregressive), depending on past information (conditional) and exhibit non-constant variance (heteroskedasticity).

Market expectations of future return volatility play a crucial role in finance and more investors have an incentive to trade the share based on diverse expectations on future returns (Ananzeh, Jdaitawi and Al-Jayousi, 2013). Volatility directly or indirectly controls asset return series, equity prices and foreign exchange rates (Hemanth and Basavaraj, 2016).

When volatility persists, securities firms are less able to use their available capital efficiently because of the need to reserve a larger percentage of cash-equivalent investments in order to reassure lenders and regulators; and greater volatility can reduce investor confidence in investing in stocks (Edwards, 2006). If volatility is changing at higher rate, it may results in high profits or huge losses (Hemanth and Basavaraj, 2016), and this should be boosted by providing empirical evidence from appropriate models.

Many people in the investing public are upset about the increased volatility, and are writing letters to congressmen, agency heads, and industry leaders to do something. The problem for those who formulate policy is that very little is known about the causes of changes in volatility of financial prices (Shiller, 2006).

The study seeks to analyse the Zimbabwe Stock Exchange, paying particular attention to the volatility of the stock market. Zimbabwe is one of the countries in Africa whose Stock market was developed a long time ago. Countries with better-developed financial systems tend to grow faster over long periods of time (Bonga, Chikeya and Sithole, 2015). Shallow financial markets and inadequate access to finance are major sources of concern in African countries generally, Adelegan (2009). Volatile international capital flows have the tendency to destabilize shallow markets and precipitate a crisis if there is a change in investors' appetite (Bonga, Chikeya and Sithole, 2015). Most studies investigating volatility in Africa focus on the biggest and most sophisticated stock markets, notable in countries like South Africa and Egypt (Cheteni, 2016).

Literature on the volatility of stock market in Zimbabwe is scarce and is to grow for better-informed investment decisions on the stock exchange. This study adds to the few prevailing studies for Zimbabwe and other neglected stock markets in Africa, operating at near levels. The volatility in developed stock markets has been comprehensively researched, while little has been done in terms of volatility in developing stock markets.

2. Overview of the Zimbabwe Stock Exchange

The Zimbabwe Stock Exchange (ZSE) is the principal stock exchange of Zimbabwe. ZSE is regulated by The Securities and Exchange Commission of Zimbabwe (SECZ). The ZSE history dates back to 1896 in Bulawayo after the arrival of the Pioneer Column (a force raised by Cecil Rhodes and his British South Africa Company in 1890 and used in his efforts to annex the territory of Mashonaland), and was open to foreign investment since 1993. The ZSE was initially Rhodesian Stock Exchange until independence in 1980. The number of listings on the ZSE is currently 64 (May 2019). The Industrial index and Mining index are the two primary indices for the ZSE. All Share index data for current years is also starting to be available.

The ZSE has foreign investment limits; 10% per individual shareholder, and 40% collectively on each listed company. Withholding tax on dividends is deducted at source, and is 15% per individual shareholder, while capital gains withholding tax is 1% of sales proceeds. Fees are determined from time to time by the Ministry of Finance and Economic Development. There is an Investor Protection Fund funded from every trade on the bourse. Buying and selling of shares is done through stock brokers registered with the ZSE. S Hyman was the first stockbroking firm in 1891, and currently stock broking firms are over 20.

On 6 July 2015, the ZSE migrated to an online trading platform through its launch of the Automated Trading System (ATS) which replaced the traditional open-outcry manual based trading. As of 23 May 2019, market capitalization stood at RTGS$ 21,030,196,647, turnover of RTGS$ 12,267,329.56, foreign buys RTGS$ 5,572,392.40, foreign sales RTGS$ 8,649,473.33 and 141 trades (ZSE website).

The ZSE commenced trading on 19 February 2009 in USD, after a brief halt between November 2008 and January 2009 due to severe economic crisis, that bedeviled the economy and led to the varnish of the Zimbabwean currency, and the formation of a government of national unity. The formal adoption of the USD as the transacting currency greatly reduced foreign exchange risk for international investors.

Mix of Local and Foreign Investors on the ZSE								
	2009	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
Local	82%	77%	64%	59%	50%	47%	44%	48%
Foreign	18%	23%	36%	41%	50%	53%	56%	52%

Table above shows growing foreign participation in the Zimbabwe Stock Market, indicating foreign acceptance of the developments in the market for the period shown by the statistics.

3. Empirical Literature Review

The concept of volatility is not new. Several studies were made in modelling the stock market volatility both in developed and in developing countries.

Murekachiro (2016), in a study, explored the comparative ability of different statistical and econometric volatility forecasting models in the context of Zimbabwe stock market. The volatility of the ZSE industrial index returns was modeled by using a univariate GARCH models both symmetric and asymmetric models namely GARCH (1,1) and EGARCH (1,1). Stock market average daily industrial index for the period 19 February 2009 to 31 December 2014 was used for analysis. The data showed a significant departure from normality and existence of conditional heteroskedasticity in the residuals series. Asymmetric EGARCH (1;1) model outperformed the symmetric GARCH (1;1) model on forecasting future volatility.

A study by Cheteni (2016), looked into the relationship between stock returns and volatility in South Africa and China stock markets, for the period January 1998 to October 2014. A GARCH model was used to estimate volatility of the stock returns, namely, the Johannesburg Stock Exchange FTSE/JSE Albi index and the Shanghai Stock Exchange Composite Index. Evidence of high volatility in both the JSE market, and the Shanghai Stock Exchange was found by the study. The analysis revealed that volatility was persistent in both exchange markets and resembled the same movement in returns.

Banumathy and Azhagaiah (2015), in their study empirically investigated the volatility pattern of Indian stock market based on time series data which consists of daily closing prices of S&P CNX Nifty Index for 10 years period from 2003 to 2012. Analysis was done using both symmetric and asymmetric models of GARCH. Using AIC and SIC, GARCH (1,1) and TARCH (1,1) were the chosen models to capture the symmetric and asymmetric volatility respectively. The study findings showed that the asymmetric effect (leverage) captured by the parameter of EGARCH (1,1) and TGARCH (1,1) models show that negative shocks have significant effect on conditional variance (volatility).

Koima, Mwita and Nassiuma (2015) in their study of the Kenyan stock market used the GARCH (1,1) model to estimate the volatility of stock returns. The GARCH (1, 1) model explained volatility of Kenyan stock markets and its stylized facts including volatility clustering, fat tails and mean reverting more satisfactorily. The study results indicated the evidence of time varying stock return volatility over the sampled period of time. In their conclusion, it follows that in a financial crisis; the negative returns shocks have higher volatility than positive returns shocks.

Khositkulporn (2013), undertook a study to identify the dominant factors affecting stock market volatility in Thailand and measure the contagion effects of stock market volatility in Thailand on other South-East Asian stock markets. Quantitative methods were adopted in testing the research hypotheses. Multiple regression and GARCH models were used to examine the factors affecting stock market volatility. Correlation coefficient and Granger causality tests were employed to hypothesis testing for contagion in South-East Asia. The study result showed that the S&P 500 had a major influence on Thailand's stock market, followed by the BSI and oil price. It was found that the movements of major stock markets and political uncertainty have direct effects on stock market volatility, and effect of movements of oil prices have an indirect effect on firm performance. The outcome of the study was tipped contributing to helping the domestic and global investors in the formulation of strategies to minimize their risk. Informing micro and macro level policy formulation by policy administrators was also tipped.

Ananzeh, Jdaitawi and Al-Jayousi (2013) investigated the empirical relationship between return volatility and trading volume using data from the Amman Stock Exchange for 27 individual stocks, using daily data for the period 2002-2012. The study results indicated that trading volume significantly contributes to the return volatility process of stocks. The study results also signify that the trading volume has no significant effect on the reduction of the volatility persistence for majority of stocks in the sample, challenging the existence of "Mixed Distribution Hypothesis" in Amman stock Exchange.

Sharaf and Abdalla (2013), modeled and estimated stock returns volatility of Khartoum Stock Exchange (KSE) Index using symmetric and asymmetric GARCH family models, namely: GARCH(1,1), GARCH-M(1,1), EGARCH(1,1) and GJR-GARCH(1,1) models. Their study used daily closing prices over the period from 2nd January 2006 to 31st August 2010. The study results revealed that a high volatility process is present in KSE Index returns series. The results also provided evidence on the existence of risk premium and indicates the presence of the leverage effect in the KSE index returns series.

Ndako (2012) employed the GARCH family to discover market volatility in South Africa. The study results indicated that there was not the estimated break coinciding with the official liberalisation dates. The analysis again showed that after taking structural breaks into account, volatility decreased following financial liberalisation. Applying official liberalisation dates, the results indicated that on the stock markets, the effect of financial liberalisation is statistically important and not positive.

Mittal, Arora, and Goyal (2012) examined the behaviour of Indian stock price and investigated to test whether volatility is asymmetric using daily returns from 2000 to 2010. The study reported that GARCH and PGARCH models were found to be best fitted models to capture symmetric and asymmetric effect respectively.

A study by Ahmed and Suliman (2011), used GARCH models to estimate volatility (conditional variance) in the daily returns of the principal stock exchange of Sudan (Khartoum Stock Exchange – KSE) over the period from January 2006 to November 2010. The study considered both symmetric and asymmetric models that capture the most common stylized facts about index returns such as volatility clustering and leverage effect. The study findings were that conditional variance process was highly persistent (explosive process), and provided evidence on the existence of risk premium for the KSE index return series which supported the positive correlation hypothesis between volatility and the expected stock returns. Asymmetric models provided a better fit than the symmetric models, which confirmed the presence of leverage effect. In conclusion, high volatility of index return series was found to be present in Sudanese stock market over the sample period.

Surya (2008), analysed the Nepalese stock market considering the anticipated growth and increasing interest of investors towards investment in Nepalese stock market. The volatility of the Nepalese stock market was modeled using daily return series consisting of 1297 observations from 2003 to 2009 and using different classes of estimators and volatility models. GARCH (1,1) model was the most appropriatel for volatility modeling in Nepalese market, where no significant asymmetry in the conditional volatility of returns was captured. Strong evidence of time-varying volatility was revealed; a tendency of the periods of high and low volatility to cluster and a high persistence and predictability of volatility in the Nepalese stock market. The study found the distribution of the daily return series for the Nepalese stock market to be leptokurtic, non-normal and exhibiting significant time dependencies.

Hammoudeh and Li (2008), using GARCH model examined stock market sensitivity to worldwide regional and local events. The study results showed that volatility was very high, even comparing with other emerging markets. The researchers found that in the Arab Gulf stock markets, as a consequence of international events, most of the volatility emergency changes.

A study by Goyal (2000), focused on the performance of various GARCH models in terms of their ability of delivering volatility forecasts for stock return data. Volatility forecasts obtained from a variety of mean and variance specifications in GARCH models were compared to a proxy of actual volatility calculated using daily data. In-sample tests suggested that a regression of volatility estimates on actual volatility produces R^2s of less than 8%. An interesting by-product was evidence of significantly negative relationship between unexpected volatility and stock returns. Out-of-sample tests indicated that a simpler ARMA specification perform better than a GARCH-M model.

The study by Kupiec (1991), characterises the historical experience of volatility in major equity markets over thirty years. It estimates changes in the historical volatilities and measures of inter-market correlations for 15 OECD countries' stock markets over alternative periods. The study focused on gross measures of volatility. The study analysis did not control for any of the events that may have contributed to financial returns volatility. The analysis suggested that the past three decades have coincided with increases in the average volatility of stock returns in most OECD countries.

Many of the reviewed literature pointed the used of GARCH family models in the volatility analysis. Different models were found appropriate for each country and period under study. This leaves our study to determine its own suitable model and verify the meaning of the model results.

4. Research Methodology

The sample period in this study span from January 2010 to January 2019, the data set is comprised of monthly returns. Data obtained from Zimbabwe Stock Exchange publications, ZIMSTAT publications and Reserve bank of Zimbabwe publications used for analysis. The ZSE has two main indices, the Industrial index and the Mining index. The study picked the Industrial Index for the volatility analysis.

4.1 Calculation of Returns

To analyse volatility the study requires calculation of returns from the stock market index. The returns are calculated using the common formula;

$$R_t = Ln(P_t / P_{t-1}) \text{ ---------- } (1)$$

Where; ***R*** is the stock return, ***P*** is the stock price and ***t*** is time.

4.2 Descriptive Statistics:

To specify the distributional properties of the monthly return series of Industrial index during the study period, the descriptive statistics are reported. The descriptive statistics will be mean, standard deviation, skewness, kurtosis and Jarque-Bera.

4.3 Stationarity Test:

Statistics require working with stationary data. The study will use the Augmented Dickey-Fuller test to test for unit root and check if data is stationary or non-stationary.

4.4 Heteroskedasticity Test:

Examining the residuals for the evidence of heteroscedasticity is important. The presence of conditional heteroskedasticity if not accounted for leads to misleading results (Iorember, Sokpo and Usar, 2017).

To test the presence of heteroscedasticity in residual of the return series, Lagrange Multiplier (LM) test for Autoregressive conditional heteroscedasticity (ARCH) is used. The Ljung Box Q statistic is an alternative test.

4.5 Volatility Measurement:

The main methodologies that are applied in modelling the stock market volatility are ARCH/GARCH models. ARCH models were introduced by Engle (1982) and generalized as GARCH by Bollerslev (1986) and Taylor (1986).

GARCH models require confirmation of ARCH effects by the ARCH-LM test. Ignoring ARCH effects may result in loss of efficiency. The study focus on determining the best fitted GARCH model to the return series.

4.6 Symmetry and Asymmetric Models

The ZSE stock market volatility has not been extensively researched and hence no strong empirical evidence available. The current study will consider both symmetric models and asymmetric models in its analysis. However, appropriate tests will be carried to determine the best model to be applied.

4.7 Post-estimation Tests

The study will carry out post-estimation tests to verify the efficiency of the models used in the study. Important for volatility models is the ARCH effects tests.

5. Data Analysis

Data analysis will be done using Microsoft Excel and Eviews statistical software.

5.1 Industrial Index Trend

The industrial index is used for the analysis. The time trend of the industrial index is shown below;

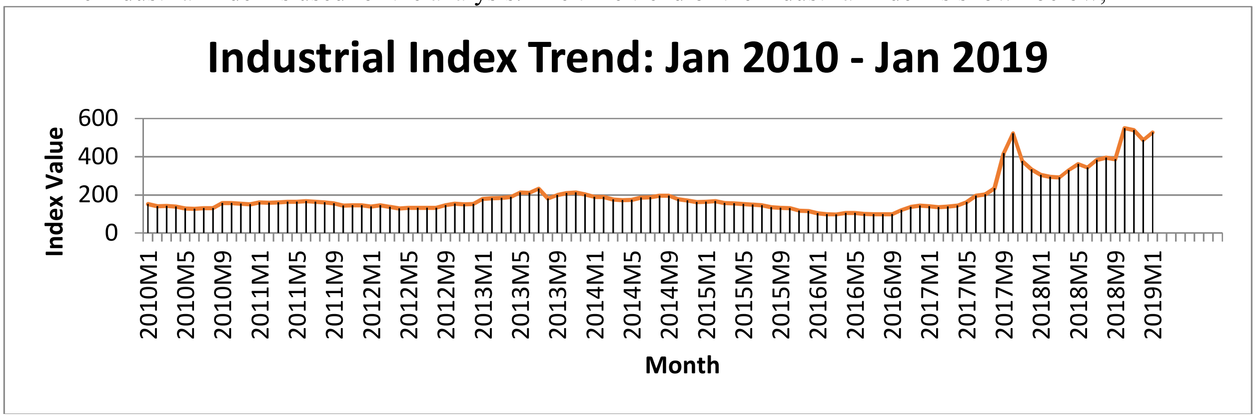
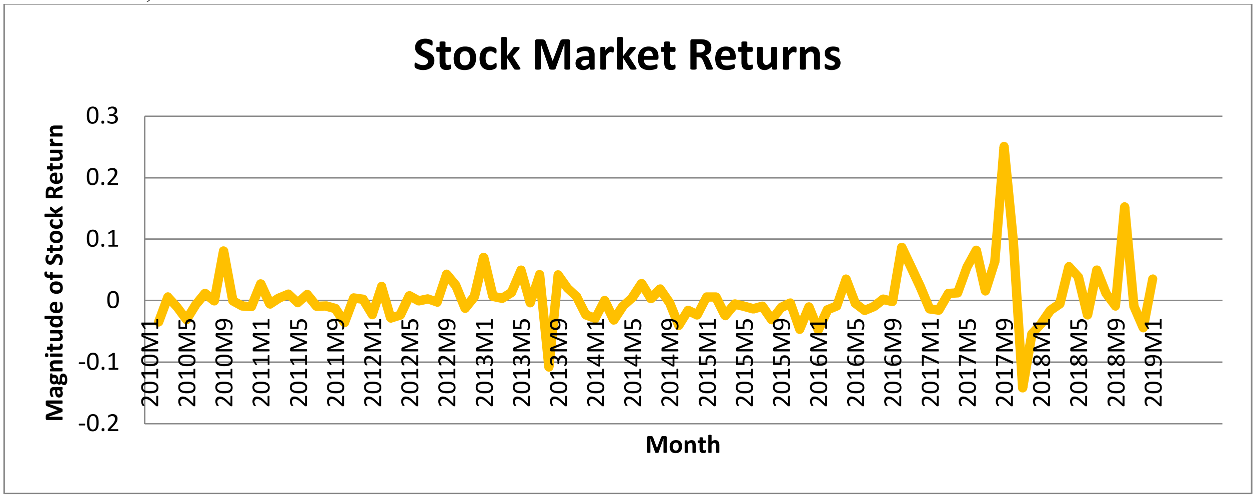


Figure above shows the trend of the industrial index over the study period. The index has been almost of the same magnitude from 2010 till 2013M1, with a slight rise till 2015M1, when there was a gentle decline upto 2016M9, with a record minimum, the index sharply rise 2017 to peak in 2017M10, declining again till 2018M4 and then rising till end year and beginning 2019. The years 2017, 2018 upto beginning 2019 is marked by high values of the index, as compared to past years.

5.2 Stock Market Returns

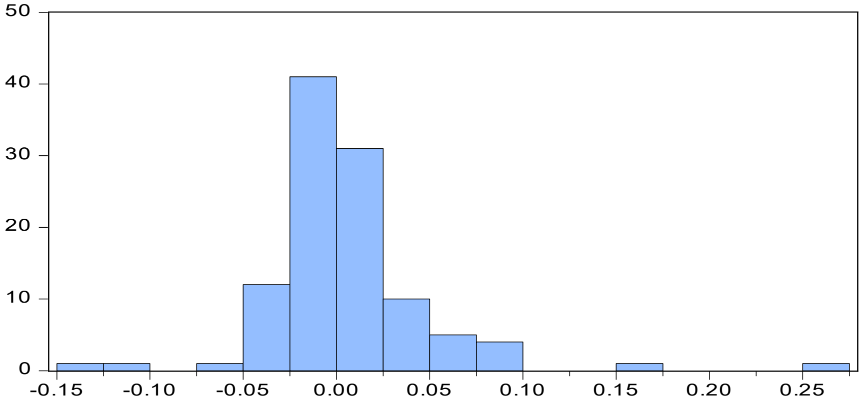
Stock market returns have been calculated from the industrial index. Returns over the period is graphically shown below;



As shown above the returns over the period has been volatile, taking positive and negative values with different magnitudes. The ups and downs in returns over the period indicates volatility in the stock market. However, by merely looking at the trend strong conclusions may not be drawn until a full statistical analysis is done.

5.3 Summary Statistics

The summary statistics of stock market returns provide critical information about volatility. The statistics are shown below;



Series: RETURNS
Sample 2010M01 2019M01
Observations 108

Mean	0.005009
Median	-0.001722
Maximum	0.250524
Minimum	-0.141592
Std. Dev.	0.044145
Skewness	1.699755
Kurtosis	12.50705
Jarque-Bera	458.7327
Probability	0.000000

The mean of the returns is positive (0.005), indicating the fact that price has increased over the period. The descriptive statistics shows that the returns are positively skewed (1.6998), indicating that there is a high probability of earning returns which is less than the mean (0.005). The kurtosis (12.507) of the return series is > 3, which implies that the return series is fat tailed and does not follow a normal distribution and is further confirmed by Jarque-Bera test statistics, which is significant at 1% level and hence the null hypothesis of normality is rejected.

5.4 Unit Root Test

Unit root test results are shown below;

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.383211	0.0000
Test critical values:	1% level	-3.492523	
	5% level	-2.888669	
	10% level	-2.581313	

The ADF statistics above (-8.38) is less than the critical values, (also p-value, 0.000 < 0.05) indicating that data is stationary. The study will work with stationary data and hence reliable results for policy will be derived.

5.5 ARCH Effects Test

The ARCH-LM test is applied to find out the presence of arch effect in the residuals of the return series. To undertook the test, firstly the model is specified as an ARIMA (1,1) model, with the help of the ACF and PACF functions. The residuals (ε_t) of the ARIMA (1,1) model are saved, and then squared (ε_t^2) to form a variable. The variance (σ_t^2) of the residuals are then calculated to form another variable. A model with the below specifications was run;

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2$$

where ω and α_i , i = 1, p are nonnegative constants. The value of p was found to be 2 with the help of ACF. After running the above equation, the ARCH-LM heteroskedasticity was done using q=12 for monthly data, hence and ARCH(12). The results of the test are shown below;

Heteroskedasticity Test: ARCH

F-statistic	30.41345	Prob. F(12,80)	0.0000
Obs*R-squared	76.27945	Prob. Chi-Square(12)	0.0000

From the ARCH-LM test above it is inferred that the test statistics is highly significant. Since $p < 0.05$, the null hypothesis of 'no arch effect' is rejected at 1% level, confirming the presence of ARCH effects in the residuals of time series models in the returns and hence the results warrant for the estimation of GARCH family models.

5.6 GARCH (1,1) Model Estimation

The basic version of the least squares model assumes that the expected value of all error terms, when squared, is the same at any given point, and this assumption is called homoskedasticity, and it is this assumption that is the focus of ARCH/GARCH models (Engle, 2001).

GARCH models treat heteroskedasticity as a variance to be modeled. GARCH (1,1) model estimation results are shown below;

Dependent Variable: RETURNS
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 05/26/19 Time: 11:12
Sample (adjusted): 2010M03 2019M01
Included observations: 107 after adjustments
Convergence achieved after 54 iterations
MA Backcast: 2010M02
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.001955	0.003810	-0.513096	0.6079
AR(1)	-0.935656	0.045638	-20.50147	0.0000
MA(1)	0.978241	0.017056	57.35489	0.0000
Variance Equation				
C	7.63E-05	3.93E-05	1.940892	0.0523
RESID(-1)^2	0.195255	0.054403	3.589068	0.0003
GARCH(-1)	0.814349	0.047161	17.26738	0.0000

R-squared	0.001739	Mean dependent var	0.005379
Adjusted R-squared	-0.017458	S.D. dependent var	0.044185
S.E. of regression	0.044569	Akaike info criterion	-3.584681
Sum squared resid	0.206583	Schwarz criterion	-3.434803
Log likelihood	197.7805	Hannan-Quinn criter.	-3.523923

Post-estimation Test: Checking on remaining ARCH effects, the test results are shown below;

Heteroskedasticity Test: ARCH

F-statistic	1.074552	Prob. F(12,82)	0.3922
Obs*R-squared	12.90895	Prob. Chi-Square(12)	0.3757

The above statistic do not indicate remaining ARCH effects, implying the GARCH estimation does not require any further modifications.

5.7 GARCH-M (1,1) Model Estimation

The return of a security may depend on its volatility (risk), and to model such phenomena, the GARCH-M model adds a heteroskedasticity term into the mean equation.

The formulation of the GARCH-M model implies that there are serial correlations in the return series. GARCH-M (1,1) model estimation results are shown below;

Dependent Variable: RETURNS
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 05/26/19 Time: 11:39
Sample (adjusted): 2010M03 2019M01
Included observations: 107 after adjustments

Convergence achieved after 46 iterations
MA Backcast: 2010M02
Presample variance: backcast (parameter = 0.7)
GARCH = C(5) + C(6)*RESID(-1)^2 + C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
GARCH	0.919672	4.355319	0.211161	0.8328
C	-0.003056	0.005940	-0.514448	0.6069
AR(1)	-0.935606	0.044697	-20.93203	0.0000
MA(1)	0.978825	0.016011	61.13426	0.0000
		Variance Equation		
C	7.58E-05	4.55E-05	1.665344	0.0958
RESID(-1)^2	0.192594	0.056638	3.400422	0.0007
GARCH(-1)	0.816139	0.054842	14.88162	0.0000

R-squared	-0.001789	Mean dependent var	0.005379
Adjusted R-squared	-0.030967	S.D. dependent var	0.044185
S.E. of regression	0.044864	Akaike info criterion	-3.566946
Sum squared resid	0.207313	Schwarz criterion	-3.392088
Log likelihood	197.8316	Hannan-Quinn criter.	-3.496061
Durbin-Watson stat	1.600562		

Post-estimation Test: Checking on the remaining ARCH effects, the test results are shown below;

Heteroskedasticity Test: ARCH

F-statistic	1.096665	Prob. F(12,82)	0.3742
Obs*R-squared	13.13785	Prob. Chi-Square(12)	0.3591

The above statistic again do not indicate remaining ARCH effects, hence the model is efficient.

5.8 Summary of GARCH(1,1) & GARCH-M (1,1) Models Estimation Results

The regression results for the two models, GARCH (1,1) and GARCH-M (1,1) are presented below;

		GARCH (1,1)	**GARCH-M (1,1)**
Mean Equation	**Constant**	-0.0020	-0.0031
	Risk Premium (λ)	-	0.09197
	AR(1)	-0.9357***	-0.9356***
	MA(1)	0.9782***	0.9788***
Variance Equation	**Constant**	7.63E-05*	7.58E-05*
	ARCH effect (α)	0.1953***	0.1926***
	GARCH effect(β)	0.8143***	0.8161***
	$\alpha + \beta$	1.0096	1.0087
Regression Statistics	**Log likelihood**	197.7805	197.8316
	SIC	-3.434803	-3.392088
	AIC	-3.584681	-3.566946
	ARCH-LM Statistics	12.90895	13.13785
	Probability	*0.3757*	*0.3591*

Discussion of Results: GARCH (1,1) is more efficient than the GARCH-M (1,1), using the AIC and SIC criterions. The AR and MA terms are all significant for both models for the mean equation. The AR terms are negative for both models, implying that past returns have negative impact. The parameter's estimates of the both GARCH(1,1) and GARCH-M (1,1) model are statistically significant. Both constants for the variance equation are approximately equal to zero; this shows that current volatility is heavily premised on squared lagged residuals and previous stock return volatility. The results also indicate that the persistence in volatility, as measured by the sum of α and β in both models, is closer to one [1.0096 & 1.0087], suggesting a stronger presence of ARCH and GARCH effects. This implies that current volatility of monthly returns can be explained by past volatility that tends to persist over time. The conclusion of persistence volatility is not a strong conclusion for this study because sum of parameters α and β is slightly larger than one [1.0096 & 1.0087], indicating that the conditional variance process is explosive.

GARCH-M (1,1) model reports a positive risk-premium (0.09197 though insignificant) indicating that data series is positively related to its volatility. The existence of risk premium is, therefore, another reason that some historical stock returns have serial correlations. These results underscore that high and low of Industrial index are associated with the rise and fall of the returns volatility, that is, an increase in the risk leads to an increase in the amount of the risk premium demanded by investors to compensate for the additional amount of risk to which they are exposed.

5.9 Integrated GARCH Model [IGARCH (1,1)]

The high persistence often observed in fitted GARCH(1,1) models suggests that volatility might be nonstationary implying that $\alpha + \beta = 1$, in which case the GARCH(1,1) model becomes the integrated GARCH(1,1) or IGARCH(1,1) model (Zivot, 2008). From the study results of the GARCH (1,1) and GARCH-M (1,1), it has been found that $\alpha + \beta \approx 1$ [1.0096 & 1.0087]. In the IGARCH(1,1) model the unconditional variance is not finite and so the model does not exhibit volatility mean reversion (Zivot, 2008). In an IGARCH model, the process is forced to act as a unit root process (Enders, 2014). Diebold and Lopez (1996) indicated that observed IGARCH behavior may result from misspecification of the conditional variance function. IGARCH is a restricted version of the GARCH model; and therefore, there is a unit root in the GARCH process and imply that current information remains of importance when forecasting the volatility for all horizons (Srinivasan, 2013).

Results of the IGARCH (1,1) model are shown below;

Dependent Variable: RETURNS
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 05/28/19 Time: 16:58
Sample (adjusted): 2010M03 2019M01
Included observations: 107 after adjustments
Convergence achieved after 28 iterations
MA Backcast: 2010M02
Presample variance: backcast (parameter = 0.7)
GARCH = C(4)*RESID(-1)^2 + (1 - C(4))*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.001316	0.000670	-1.964789	0.0494
AR(1)	0.906281	0.017879	50.68987	0.0000
MA(1)	-0.973850	0.004028	-241.7549	0.0000
		Variance Equation		
RESID(-1)^2	0.142664	0.023098	6.176365	0.0000
GARCH(-1)	0.857336	0.023098	37.11668	0.0000
R-squared	-0.142033	Mean dependent var		0.005379
Adjusted R-squared	-0.163995	S.D. dependent var		0.044185
S.E. of regression	0.047670	Akaike info criterion		-3.440468
Sum squared resid	0.236336	Schwarz criterion		-3.340549
Log likelihood	188.0651	Hannan-Quinn criter.		-3.399962
Durbin-Watson stat	1.306923			

Post-estimation Test: Checking on the remaining ARCH effects, the test results are as follows;

Heteroskedasticity Test: ARCH

F-statistic	0.723402	Prob. F(12,82)	0.7247
Obs*R-squared	9.094299	Prob. Chi-Square(12)	0.6949

The above statistic again do not indicate remaining ARCH effects, hence the model is efficient.

Discussion of Results: The parameter estimates of the IGARCH (1,1) model reported above are all significant. In conditional variance equation, the coefficient of β (0.857) were found to be significant at 1% level, inferring that the market takes some time to digest the full information into the prices; and shocks to conditional variance takes a long time to die out.

5.10 Asymmetric Model: EGARCH (1,1) Model

GARCH (1;1) model does not consider the leverage effect; it assumes that positive and negative shocks have the same impact on stock market. This assumption is not valid because under normal circumstances these shocks do have different effect on stock market volatility (Murekachiro, 2016). The application of Exponential-GARCH (EGARCH) will solve the weakness of GARCH model.

The results of the EGARCH (1,1) are shown below;

Dependent Variable: RETURNS
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 05/28/19 Time: 15:57
Sample (adjusted): 2010M03 2019M01
Included observations: 107 after adjustments
Convergence achieved after 132 iterations
MA Backcast: 2010M02
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.035674	527.1191	0.003862	0.9969
AR(1)	1.000116	0.029943	33.40029	0.0000
MA(1)	-0.958800	0.007761	-123.5423	0.0000
		Variance Equation		
C(4)	0.088749	0.147122	0.603238	0.5464
C(5)	-0.187740	0.094901	-1.978268	0.0479
C(6)	0.171352	0.045756	3.744940	0.0002
C(7)	0.993999	0.016488	60.28587	0.0000

R-squared	-0.038918	Mean dependent var	0.005379
Adjusted R-squared	-0.058897	S.D. dependent var	0.044185
S.E. of regression	0.045467	Akaike info criterion	-3.879111
Sum squared resid	0.214997	Schwarz criterion	-3.704253
Log likelihood	214.5324	Hannan-Quinn criter.	-3.808226
Durbin-Watson stat	1.599348		

Post-estimation Test: Post-estimation test results for further ARCH effects is shown below;

Heteroskedasticity Test: ARCH

F-statistic	0.448320	Prob. F(12,82)	0.9382
Obs*R-squared	5.849001	Prob. Chi-Square(12)	0.9235

Post-Estimation Test Interpretation: The result presented above shows that, the F-statistic value 0.44832 and its probability of 0.9382 provides evidence to accept the null hypothesis of no ARCH effect in the model. The presented model is therefore free from conditional heteroskedasticity and therefore reliable for policy.

Discussion of Results: The EGARCH (1,1) proved to be more efficient than the GARCH (1,1) and GARCH-M (1,1), as shown by the AIC and BIC criterions [-3.879 &-3.704]. The persistence parameter, C(7) = 0.994 (0.0000), is very large, implying that the variance moves slowly through time. The coefficient C(6) = 0.171352 measures the presence of asymmetry; it is statistically significant implying the presence of asymmetry and hence the EGARCH model is more efficient than GARCH model. The asymmetry coefficient, C(6), is positive, implying that the variance goes up more after positive residuals than after negative residuals. Positive and negative shocks have different effects on the stock market returns series. Bad and good news will increase volatility of stock market returns in different magnitude. This simply imply that investors on the Zimbabwean stock exchange react differently to information depending be it positive or negative in making investment decisions.

6. Conclusion

Modelling and forecasting volatility of a financial time series has become a fertile area for research (Ahmed and Suliman, 2011). Volatility in speculative markets seems to be viewed by the public as a legitimate concern of government regulators, and so any increase in volatility in markets tends to be accompanied by public demands on regulators (Shiller, 2006). The study managed to explore volatility of the Zimbabwean Stock market using both symmetric and asymmetric models after testing the presence of ARCH effects. The study estimated the GARCH (1,1), GARCH-M (1,1), IGARCH (1,1) and the EGARCH (1,1) models. The Exponential GARCH (1,1) model proved to be the efficient model for modelling volatility, with asymmetric coefficient being significant. The study concludes that positive and negative shocks impact differently on the stock market returns. Bad and good news will increase volatility of stock market returns in different magnitudes. The study results implies that the investment climate including the stability in the macroeconomic environment should be favourable to ensure growth in the stock market. Investors require the predictability of the future to make sound investment decisions. Policies to reduce volatility in the stock market are a necessity for the economy.

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APPENDIX A: MONTHLY INDUSTRIAL INDEX FOR ZIMBABWE STOCK MARKET

MONTH	INDEX	MONTH	INDEX	MONTH	INDEX	MONTH	INDEX	MONTH	INDEX
2010M1	151.99	**2011M11**	144.98	**2013M10**	209.74	**2015M9**	131.93	**2017M8**	235
2010M2	140.37	**2011M12**	145.86	**2013M11**	213.04	**2015M10**	130.83	**2017M9**	418.4
2010M3	142.37	**2012M1**	138.52	**2013M12**	202.12	**2015M11**	117.55	**2017M10**	521.9
2010M4	139.01	**2012M2**	146.03	**2014M1**	189.25	**2015M12**	114.85	**2017M11**	376.7
2010M5	129.4	**2012M3**	136.76	**2014M2**	189.45	**2016M1**	103	**2017M12**	333
2010M6	127.46	**2012M4**	129.55	**2014M3**	176.32	**2016M2**	99.5	**2018M1**	305.4
2010M7	130.92	**2012M5**	132.03	**2014M4**	172.91	**2016M3**	97.6	**2018M2**	294.6
2010M8	130.92	**2012M6**	131.96	**2014M5**	174.89	**2016M4**	105.8	**2018M3**	291
2010M9	157.7	**2012M7**	132.92	**2014M6**	186.57	**2016M5**	104.7	**2018M4**	330.7
2010M10	157.7	**2012M8**	132.27	**2014M7**	188.07	**2016M6**	101	**2018M5**	361.5
2010M11	154.6	**2012M9**	146	**2014M8**	196.43	**2016M7**	98.8	**2018M6**	342.8
2010M12	151.3	**2012M10**	154.47	**2014M9**	195.25	**2016M8**	99.3	**2018M7**	384.3
2011M1	161.1	**2012M11**	150.16	**2014M10**	177.88	**2016M9**	99	**2018M8**	394.6
2011M2	159.04	**2012M12**	152.4	**2014M11**	171.45	**2016M10**	120.8	**2018M9**	387
2011M3	160.65	**2013M1**	179.34	**2014M12**	162.57	**2016M11**	137.1	**2018M10**	549.8
2011M4	164.64	**2013M2**	182.3	**2015M1**	164.9	**2016M12**	144.5	**2018M11**	538.7
2011M5	163.37	**2013M3**	183.88	**2015M2**	167.16	**2017M1**	140.2	**2018M12**	487.1
2011M6	167.18	**2013M4**	189.66	**2015M3**	158.22	**2017M2**	135.3	**2019M1**	528.2
2011M7	163.69	**2013M5**	212.72	**2015M4**	156.23	**2017M3**	139		
2011M8	160.53	**2013M6**	211.19	**2015M5**	152.96	**2017M4**	143.2		
2011M9	155.82	**2013M7**	232.87	**2015M6**	148.4	**2017M5**	162.3		
2011M9	155.82	**2013M8**	181.67	**2015M7**	145.35	**2017M6**	196		
2011M10	143.58	**2013M9**	200.05	**2015M8**	135.43	**2017M7**	203.3		