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Time Series Volatility Forecasting of the Zimbabwean Stock Exchange

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Abstract:

This paper attempts to explore the comparative ability of different statistical and econometric volatility forecasting models in the context of Zimbabwe stock market. Two different models were considered in this study. The volatility of the ZSE industrial index returns have been modeled by using a univariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models including both symmetric and asymmetric models that captures most common stylized facts about index returns such as volatility clustering, fat tails and leverage effect, these models are GARCH (1,1) and exponential GARCH (1,1). The first model is used for capturing the symmetry effect whereas the second model is for capturing the asymmetric effect.

The study used a stock market average daily industrial index from Zimbabwe (ZSE index), a country not previously considered in the volatility literature, for the period 19 February 2009 to 31 December 2014. Basing on the empirical results presented, the following can be concluded. ZSE data showed a significant departure from normality and existence of conditional heteroskedasticity in the residuals series. For all periods specified, the empirical analysis evidenced that asymmetric EGARCH (1;1) model outperform the symmetric GARCH (1;1) model on forecasting future volatility after using two different evaluation techniques of Error measures statistics and regression based analysis.

Future studies should consider the general extensions of GARCH models, in particular symmetric and asymmetric GARCH (p; q) rather than symmetric and asymmetric GARCH (1;1) model. This general extension is helpful because such higher order-models are often useful when long span of data is used. Therefore, with additional lags such models allow both fast and slow decay of information.

Keywords: volatility, GARCH, Stylised facts

1. Introduction

Over the last few years, modeling and forecasting volatility of a financial time series has become a fertile area for research due to the fact that volatility is considered as an important concept for many economic and financial applications. According to Poon (2005), volatility means the conditional variance of the underlying asset return. A special feature of this volatility is that it is not directly observable, so that financial analysts are very keen to obtain a precise estimate of this conditional variance process.

As proposed by Akgiray (1989), capital market volatility may be conceived of as a degree to which asset prices tend to fluctuate and it is described as the variability or randomness of asset prices. Thus volatility is often described as the rate and magnitude of changes in prices and in finance often referred to as risk. In other words, volatility according to public perspectives mean days when large market movements, particularly down moves, occur Miller (1988). These precipitous market wide price drops cannot always be traced to a specific news event. Nor should this lack of smoking gun be seen as in any way anomalous in market for assets like common stock whose value depends on subjective judgment about cash flow and resale prices in highly uncertain future. The public takes a more deterministic view of stock prices; if the market crashes, there must be a specific reason.

Thus, to a certain extent market volatility is unavoidable, even desirable, as the stock price fluctuation indicates changing values across economic activities and it facilitates better resource allocation. But frequent and wide capital market variations cause uncertainty about the value of an asset and affect the confidence of the investor. The risk averse and the risk neutral investors usually withdraw from the market at sharp price movements thereby disrupting the smooth functioning of the capital market.

Many time series occurring in the natural sciences and financial engineering cannot be modeled by linear processes. These kinds of time series can be best modeled by nonlinear processes. Due to the above, a number of models have been developed that are specifically suited to estimate the conditional volatility of financial instruments, of which the most well-known and frequently applied models for this volatility are the conditional heteroskedastic models. Among these models are, the Autoregressive Conditional Heteroskedasticity (ARCH) model proposed by Engle (1982) and its extension; Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model by Bollerslev and Taylor (1986), were found to be the first models introduced into the literature and have become very popular in that they enable the analysts to estimate the variance of a series at a particular point in time Anderson (2004). These types of models were designed to explicitly model and forecast the time-varying conditional second order moment (variance) of a series by using past unpredictable changes in the returns of that series.

Under normal market conditions, portfolio managers, brokers and investors in particular should obtain a more efficient portfolio allocation, better risk management framework and more accurate prices of a certain financial instruments in order to forecast and make meaningful decisions for the future. However, due to instability of prices and market returns, increased volatility is experienced. This study therefore attempts to close the gap in determining the best model of forecasting capital market volatility to aid on efficient allocation of resources for investment. To this end, the study sought to identify and estimate the conditional variance of Zimbabwe daily stock prices, to explore the main effects of stock market volatility on the Zimbabwean Economy, to identify the best performing volatility model for Zimbabwean stock market and to explore the reasons of Zimbabwe stock return volatility.

2. Literature Review

According to Poon (2005), financial volatility can be defined as the dispersion of the underlying asset return over a specific time period. Volatility can be statistically measured as the variance of a sample data set σ^2 , which is calculated from a number of observations as follows;

$$\sigma^2 = \frac{1}{T-1} \sum_{t=1}^T (R_t - \mu)^2 \dots \dots (1)$$

Where μ is the mean return over the T-day period; R_t is the return at the time t . However, volatility and standard deviation are considerably different, which is necessary to point out. The standard deviation of a sample exhibits the second moment characteristic of the sample. In fact, from the above equation σ can be computed from any distribution of underlying assets.

one stylised fact about volatility is the presence of volatility clustering where large (small) movements tend to be followed by large (small) movements. Engle (1982) proposes to capture this property with Autoregressive Conditional Heteroskedasticity (ARCH) model. The ARCH (q) is formulated as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 \dots \dots \dots (2)$$

Where σ_t^2 is the conditional variance at time t ; ε_t^2 is the squared error term and q is the number of lags. In this model, the volatility clustering is modelled by allowing the error variance to depend on q lags of squared residual terms. Since the value of the conditional variance σ_t^2 must always be positive while it consists of all squared error terms which are not negative, the model requires all the coefficients to be non-negative $\alpha_i \geq 0 \forall i = 0, 1, 2, \dots, q$ (Brooks, 2008).

The ARCH (q) model is extended by Bollerslev (1986) and Taylor (1986) to the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) (p, q) which is specified as follows.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2 \quad (3)$$

Where ε_{t-1} is the lagged error term; α and β are the parameters to be estimated; p and q are the number of autoregressive and moving terms respectively and the sum of coefficients α_i and β_j must be less than 1. In this model, the current conditional variance depends on q lags of the past squared error and p lags of the past conditional variance which capture high frequency effects and long term influences respectively (Figlewski, 1997). Financial time series are known to exhibit volatility clustering. However, it was only when the ARCH model was introduced that this property has been modelled. Despite GARCH-type models' popular applications in modelling the volatility of asset prices, there are a few studies reporting them to have poor predictive ability and favouring the historical volatility or stochastic volatility models instead (Tse, 1991; Figlewski, 1997; Yu, 2002).

However, most studies show that GARCH models provide superior forecasting accuracy. For instance, Erdington and Guan (2004) evaluate the forecasting performance of a number of models including the historical volatility, the EWMA and GARCH (1;1) across different financial series such as the U.S stock index, the exchange rate and the bond rate. The authors find that GARCH consistently has the best in-sample performance among these three models. Similar finding is observed for the out-of-sample evaluation.

Among the GARCH family, many researchers share the same conclusion that GARCH (1;1) yields better forecasts. Gokcan (2000) compares the forecasting abilities of both linear (GARCH (1;1)) and non-linear (EGARCH) models of GARCH family in seven emerging markets from 1988 to 1997. Contrary to the common viewpoint that linear GARCH models cannot cope with serious skewness in the financial returns, he finds that GARCH (1;1) shows superiority to EGARCH in both within-sample and out-of-sample even if the return series exhibit significant skewness. It is, however, noted that he only uses the AIC statistic to evaluate the performance of models. Other studies with similar findings are Doidge and Wei (1998), Erderington and Guan (2000), and McMillan et al. (2000).

However, many studies have shown favour to EGARCH. In his study, Najand (2002) examines the forecasting accuracy of various models ranging from linear models and non-linear models for S&P 500 futures index from 1983 to 1996. He finds that non-linear models such as GARCH-M and E-GARCH models dominate linear models and within the non-linear category EGARCH is clearly the best performing model. Najand (2002) continue to examine the predictive ability of GARCH models at different forecast horizons by conducting pair wise comparisons of various models with the benchmark as GARCH (1;1) and then a joint comparison of all models. He shows that asymmetric GARCH models clearly outperform GARCH (1;1).

Alberg et al., (2008) aim to evaluate the forecasting performance of GARCH, EGARCH, GJR and APARCH models coupled with different densities. The authors use daily data of the two major Tel-Aviv stock exchange indices – TA100 and TA25 from 1992 to 2005. They show that the traditional GARCH model has the least accurate forecast as compared to the other three models. Additionally, they also found that models with the Student's t distribution perform better than those with the normal distribution. They conclude EGARCH with the Student's t density function is the best forecaster as they can characterise some dynamic behaviours of the returns series such as auto-correlation, asymmetric volatility clustering and leptokurtosis. In line with these findings are Cao and Tsay (1992), Loudon et al. (2000).

By using asymmetric GARCH models, Alberg et al. (2006) estimate stock market volatility of Tel Aviv Stock Exchange (TASE) indices, for the period 1992-2005. They report that the EGARCH model is the most successful in forecasting the TASE indices. Various time series methods are employed by Tudor (2008), including the simple GARCH model, the GARCH-in-Mean model and the Exponential GARCH to investigate the Risk-Return Trade-off on the Romanian stock market. Results of the study confirm that EGARCH is the best fitting model for the Bucharest Stock Exchange composite index volatility in terms of sample-fit.

Conditional volatility has been initially tested starting from real data taken from the US stock market. Later on, the same econometric models were applied in other stock markets, such as the Netherlands (de Jong *et al.*, 1992), Japan (Tse, 1991), Singapore (Tse and Tung, 1992) or UK (Poon and Taylor, 1992). The few papers that attempted to test the predictive capacity of ARCH models have found inconsistent results. For example, Akgiray (1989) concluded that a GARCH (1;1) specification showed a better forecasting capacity when compared to other traditional models, when tested with US data.

Other models such as GJR-GARCH or MRS-GARCH are also evidenced to have superior forecasting performance in some studies such as Engle and Ng (1991), Bali (2000), Taylor (2001) or Marcucci (2005). Generally, findings from the international markets are inconsistent with mixed results observed for the same models or for the same markets. Similar evidences are found in the South East Asian markets. Among the evidence that highlights the superiority of more complex models (although in some points there are some consistencies in findings with the previous mentioned evidence), there is Brailsford and Faff (1995), who, by using Australian data, showed empirically that more advanced ARCH class models and a simple regression model provided superior forecasts of volatility. A second finding of them would be that the various model rankings are sensitive to the choice of error statistic, used to assess the accuracy of forecasts. Of course, when bringing into discussion the results of Brailsford and Faff (1995), the researcher makes a strong assumption that using different pools of data (Australian and UK) does not affect the quality of the models tested. This means that, if doing Brailsford and Faff (1995) analysis with UK data and Dimson and Marsh (1996) with Australian data, their conclusions would still hold.

Gregory et al. (1996) examined how volatility of S&P 500 Index futures affects the S&P 500 Index volatility. Their study also examined the effect of good and bad news on the spot market volatility. Using EGARCH model they concluded that bad news increases volatility more than good news and the degree of asymmetry is higher for futures market.

Engle and Rangel (2004) introduced a new model to measure unconditional volatility, the Sp line-GARCH. The model is applied to equity markets for 50 countries for up to 50 years of daily data. Macro-economic determinants of unconditional volatility are investigated. It is found that volatility in macro-economic factors such as GDP growth, inflation and short term interest rates are important explanatory variables that increase volatility. There is evidence that high inflation and low growth of output are positive determinants. Volatility is higher for emerging markets and for markets with small numbers of listing but also for large economies. Batra (2004) examined the economic significance of changes in the pattern of stock market volatility in India during 1979-2003. The analysis reveals that the period around the BOP crisis and the initiation of economic reforms in India is the most volatile period in the stock market.

Kohers et al. (2005) examined the stock market volatility for different countries over time which reveals important evidence on the changing nature of the risk and return trade-off in different markets. In analyzing this issue, the study examines the changes in stock price fluctuations in the world's emerging stock markets over the period from 1988 through June 2004. Their findings show common trends in the risk and return characteristics of these diverse emerging markets over time.

Padhi (2005) explained the stock market volatility at the individual script level and at the aggregate indices level. The empirical analysis has been done by using ARCH, GARCH model and ARCH in Mean model and it is based on daily data for the time period from January 1990 to November 2004. The analysis reveals the same trend of volatility in the case of aggregate indices and five different sectors such as electrical, machinery, mining, non-metallic and power plant sector. The GARCH (1, 1) model is persistent for all the five aggregate indices and individual company.

Kasch-Haroutounian and Price (2001), Gilmore and McManus (2001), Poshakwale and Murinde (2001.) and Murinde and Poshakwale (2002) investigated the volatility of Central and Eastern European stock markets and found high volatility persistence, significant asymmetry, lack of relationship between stock market volatility and expected return and non-normality of the return distribution to be the basic characteristics of stock market volatility in those countries.

It is noted that the Asian markets have not been extensively investigated, especially the Indonesian stock market which has not been discussed in any previous paper. Among few studies on the Asian stock markets, the authors also present conflicting results. For the Malaysian market, Haniff and Pok (2010) employ GARCH, EGARCH and TGARCH to model the volatility of the Malaysian stock index from 2001 to 2002 with 5-minute frequency data. They find that EGARCH consistently outperforms the other two GARCH-type models. However, other studies have presented different results.

Angabini and Wasiuzzaman (2011) sample the stock returns from 2000 to 2007 to examine the volatility movement in the Malaysian stock market. They evaluate the predictive powers of GARCH (1;1), EGARCH and GJR-GARCH with the measures such as RMSE,

MAE, MAPE and TIC. All these four statistics reach the same conclusion that GARCH (1;1) is the best performing model even though the return series exhibits asymmetry and leverage effect.

Using the daily data set from the Malaysian stock index for the period of 1998 to 2008, Shamiri and Isa (2009) compare the performance of alternative GARCH-type models (the symmetric GARCH versus the asymmetric EGARCH and NAGARCH) with different densities (normal versus non-normal). The authors show that for the in-sample data set, the EGARCH model with non-normal distributions outperforms all the remaining models and distributions. However, for the out-of-sample data set, no particular model shows its superior forecasting performance. They argue that generally, asymmetric models with a Student's t distribution assumption perform better.

Gokcan (2000) includes Malaysia and Philippines in his study on seven emerging markets. With the return data from 1988 to 1997, he compares the performance of EGARCH model with the linear GARCH model. For the in-sample estimation, the author finds that GARCH (1;1) shows its superiority over EGARCH. The result is also replicated for the out-of-sample data set. Generally, in both the Malaysian and Filipino markets, GARCH (1;1) is the most effective model in forecasting volatility

For the Singaporean market, Kuen and Hoong (1992) employ three forecasting methods namely the naïve method, the exponentially weighted moving average method and GARCH model and find that EWMA is strongly favoured. Bala and Premaratne (2004) use GARCH, EGARCH and GJR-GARCH for the daily returns over a period of 10 years from 1992 to 2002 in Singapore and some other markets to examine the volatility dynamics among these countries. They find that the GJR-GARCH performs better for the Singaporean market.

However, using the data covering 10 years from 1999 to 2009, Guidi (2010) evaluates the forecasting performance of volatility models including several GARCH models. Results from 3 out of 4 error measures indicate models with the normal distribution specification outperform other models. Besides, Guidi (2010) also finds RMSE, MAE and TIC measures imply that symmetric GARCH models have better performance while MAPE statistic favours the asymmetric one. He concludes that symmetric GARCH models with the normal distribution are preferred for forecasting the volatility in the Singaporean stock market.

Xu (1999) and Lee et al. (2001) came up with two papers that estimate volatility for stock markets in China. Xu (1999) modeled volatility for daily spot returns of Shanghai composite stock index from May 21, 1992 to July 14, 1995 and tested the in-sample goodness-of-fit of various competing models. He found that the GARCH model is superior to that of Stochastic Volatility SV, EGARCH or GJR-GARCH models, indicating that there is almost no so-called leverage effect in the Shanghai stock market since volatility is mainly caused by governmental policy on stock markets under the present financial system. The papers by Xu (1999) and Lee et al. (2001) just focus on the in-sample goodness-of-fit of volatility models. However, a good starting point to judge competitive models is to assess their out-of-sample forecasting performance. In addition, a leptokurtic and skewed returns distribution should be considered when using emerging market data.

Lee et al. (2001) examined time-series features of stock returns and volatility in four of China's stock exchanges. They provided strong evidence of time-varying volatility and indicated volatility is highly persistent and predictable. Moreover, evidence in support of a fat-tailed conditional distribution of returns was found. By employing eleven models and using symmetric and asymmetric loss functions to evaluate the performance of these models, Balaban and Faff (2003) forecasted stock market volatility of fourteen stock markets. According to symmetric loss functions the exponential smoothing model provides the best forecast.

However, when asymmetric loss functions are applied ARCH-type models provide the best forecast. Balaban and Bayar (2005) used both symmetric and asymmetric ARCH-type models to derive volatility expectations. The outcome showed that there was a positive effect of expected volatility on weekly and monthly stock returns of both Philippines and Thailand markets according to ARCH model. The result is not clear if using the other models such as GARCH, GJR-GARCH and EGARCH.

Working with Asian data, Tse (1991) and Tse and Tung (1992) came with opposite results, questioning the superiority of GARCH model. However, all three studies were converging in one result, namely that the exponential weighted moving average (EWMA) model was among the best forecasting models. To sum up what we stated above, the present literature written on this topic contains contradictory evidence with regards to the quality of the market volatility forecasts. The main message is that volatility forecasting is a notoriously complicated undertaking. There is evidence that underlines the superiority of more complex models such as ARCH models, while there is evidence on the other side as well, underlying the superiority of more simple alternatives. This is seen as an extremely problematic fact due to the difficulty that this contradiction rises in choosing the appropriate model in volatility forecasting in decision-making and analysis activities.

Chan et al. (1991) estimated the intraday relationship between returns and returns volatility in the stock Index and stock Index futures. Their study covered both S&P500 and Major Market Index (MMI) futures. Using Bi-Variate GARCH models to estimate volatility, they conclude a strong inter-market dependence in volatility of spot and futures returns. In their study on the calendar effects in the Thai stock market, Holden et al. (2005) also examine the forecasting accuracy of GARCH-type models such as GARCH (1;1), GARCH-M and TGARCH. The authors point out that including calendar effects improves the forecasting accuracy. Besides, when the calendar effects are ignored, GARCH (1;1) shows its superiority over the other two models. They also find that GARCH-M has a poor forecasting performance.

Choudhry et al. (1996) conducted a study on volatility, risk premium and the persistence of volatility in emerging stock markets before and after the stock market crash of 1987. The market data were taken from Argentina, Greece, India, Mexico, and Thailand. The results show changes in the ARCH parameter, risk premium and persistence of volatility before and after the 1987 crash. However, the changes are not uniform and depend upon the individual markets. Furthermore, other factors may also have contributed to the changes.

Kim and Singal (1997) and De Santis and Imorohoroglu (1994) studied the behaviour of stock prices following the opening of a stock market to foreigners or large foreign inflows. They find that there is no systematic effect of liberalization on stock market volatility. These findings corroborate Bekaert's findings that volatility in emerging markets is unrelated to his measure of market integration.

Hansen and Lunde (2001) evaluated the relative performance of the various volatility models for Asian markets in terms of predictive ability of realized volatility by using the tests developed by White (2000) and Hansen (2001) called as data snooping tests. Unfortunately, as pointed out by Bollerslev, Engle and Nelson (1994) and by Diebold and Lopez (1996), it is hard to say which criteria are the best to use when comparing volatility measures. Hansen and Lunde (2001) used seven different criteria for such comparison, which included standard criteria such as mean squared error (MSE) criterion, a likelihood criterion, and the mean absolute deviation criterion which was less sensitive to extreme mis-predictions, compared to the MSE. Thus, they considered a benchmark model and an evaluation criterion and tests for data snooping. This allowed them to know whether any of the competing models were significantly better than the benchmark. The benchmark models considered were ARCH (1;1) and GARCH (1;1) models. Their findings showed the superiority of all models as compared to ARCH (1;1), but GARCH (1;1) was not significantly outperformed in each stance. Although the analysis in one data set clearly indicated the existence of one superior model as compared to GARCH (1;1) when using the mean squared forecast error as a criterion, this did not hold up to other type of criteria that seemed to be more robust to outliers, such as the mean absolute deviation criterion.

Aggarwal et al. (1999) explored the stock market volatility of 10 largest emerging markets in Asia and Latin America. They found that shifts in volatility of considered emerging markets is related to important country-specific political, social, and economic events. Moreover, the time-varying stock market volatility is modeled by GARCH models.

Deb, Vuyyuri and Roy (2003) modeled the monthly volatility of market indices (Sensex & S&PCNX-Nifty) of Indian capital markets using eight different univariate models. Out-of-sample forecasting performance of these models has been evaluated using different symmetric, as well as asymmetric loss functions. The GARCH (1;1) model has been found to be the overall superior model based on most of the symmetric loss functions, though ARCH has been found to be better than the other models for investors who are more concerned about under predictions than over predictions. Karmakar (2006) measured the volatility of daily stock return in the Indian stock market over the period of 1961 to 2005. Using GARCH model, he found strong evidence of time varying volatility. He also used the TGARCH model to test the asymmetric volatility effect and the result suggests the asymmetry in volatility.

Rao, Kanagaraj and Tripathy (2008) attempts to determine the impact of individual stock futures on the underlying stock market volatility in India by applying both GARCH and ARCH model for a period of seven years from June 1999 to July 2006. This study includes stock of 10 companies that is Reliance, SBI, TISCO, ACC, MTNL, TATA Power, TATA Tea, BHEL, MAHINDRA & MAHINDRA and ITC. The results suggest that stock future derivatives are not responsible for increase or decrease in spot market volatility and conclude that there could be other market factors that have helped the increase in Nifty volatility.

Hansen and Lunde (2001) who used intra-day estimated measures of volatility to compare volatility models. Their objective was to evaluate whether the evolution of volatility measures has led to better forecasts of volatility when compared to the first "species" of volatility models. For this, they compared two different time series, daily exchange rate data and stock prices. Their findings showed that the more advanced models did not provide better forecasts than GARCH (1;1) model.

For emerging African markets, Ogum and Nouyrigat (2005) investigate the market volatility using Nigeria and Kenya stock return series. Results of the Exponential GARCH model indicate that asymmetric volatility found in the U.S. and other developed markets is also present in Nigerian stock exchange, but Kenya shows evidence of significant and positive asymmetric volatility. Also, they show that while the Nairobi Stock Exchange return series indicate negative and insignificant risk-premium parameters, the Nigerian stock exchange return series exhibit a significant and positive time-varying risk premium.

In the return series of Nairobi stock exchange, the order (1;1) is the best choice. Comparing the diagnostics and the goodness of fit statistics, the IGARCH (1;1) outperformed the ARCH, EGARCH and TGARCH models majorly due to its stationarity in the strong sense. However, the IGARCH model is unable to capture the asymmetry exhibited by the stock data. The EGARCH (1,1) and the TGARCH (1,1) are the preferred models to describe the dependence in variance for all the return series studied since they were able to model asymmetry and parsimoniously represent a higher order ARCH(p). However, the standardised residuals still displayed non-normality in all cases.

Suliman (2011) attempts to explore the comparative ability of different statistical and econometric volatility forecasting models in the context of Sudanese stock market namely; Khartoum Stock Exchange. A total of five different models were considered in his study. The volatility of the Khartoum Stock Exchange index returns have been modeled by using a univariate Generalized Autoregressive Conditional Heteroskedastic (GARCH) models including both symmetric and asymmetric models that captures most common stylized facts about index returns such as volatility clustering and leverage effect, these models are GARCH(1;1), GARCH-M(1;1), exponential GARCH(1;1), threshold GARCH(1;1) and power GARCH(1;1). The first two models are used for capturing the symmetry effect whereas the second group of models is for capturing the asymmetric effect. The study used a stock market index from Sudan (Khartoum Stock Exchange index), for the period 2nd January 2006 to 30th November 2010. The empirical findings exhibit the superiority of asymmetric GARCH models where EGARCH (1;1) taking the lead on all other GARCH models.

In a study of stock return volatilities in low-income African emerging markets using monthly market indices for the Ghanaian stock market (1991-1996), Nigerian stock market (1984-1995), and Zimbabwean stock market (1987-1995), Ayadi, (1998) find that the results of both the Kruskal-Wallis and Friedman tests suggest the absence of volatility in stock returns on the Nigerian and Zimbabwean stock markets while the Friedman test confirms the presence of volatility in stock returns for Ghana.

In a more recent study, using weekly index returns adjusted for thin trading as a nonlinear autoregressive process with conditional heteroscedasticity, Kamakar (2006) used the EGARCH-M model to investigate the volatility of eleven African stock markets. Their

findings reject evidence in prior studies that the Nigerian stock market signifies low volatility. They confirm ex ante results that the markets in Egypt, Kenya, Zimbabwe, Mauritius and Morocco are efficient while that of South Africa, Mauritius and Morocco, Botswana, Ghana, Ivory Coast, and Swaziland are not. The efficient results scenario indicates that investors can carry out efficient portfolio allocation since markets are relatively stable.

3. Methodology

3.1. Exponential-Garch (1;1)

ARCH and GARCH are known to be able to remove the excess kurtosis in the return series; however, they fail to deal with the skewness distribution (Chong et al. 1999). To address this limitation, Nelson (1991) constructs Exponential-GARCH (EGARCH) to capture the asymmetric effects on the conditional variance which GARCH fails to handle. EGARCH (1;1) is specified in the form of logarithm of the conditional variance as follows:

$$\ln(\sigma_t^2) = \alpha_0 + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \dots \dots \dots (4)$$

Where σ_t^2 is the conditional variance at time t ; $\alpha_0, \alpha_1, \beta$ and γ are coefficients to be estimated; and ε_t is the error term at time t . Since the logarithmic format ensures that conditional variance is always positive even if the parameters are negative, it does not require imposing non-negativity restrictions on the parameters. Besides, the standardised value of residual ε is used instead of the squared residuals and this can allow for more natural interpretation of the size and persistence of shocks (Nelson, 1991). The model allows the leverage effect through the parameter γ . If $\gamma = 0$, both positive and negative shocks have the same impact on the volatility; whereas, if $\gamma < 0$, negative shocks cause a greater volatility than positive shocks of the same magnitude and vice-versa in case $\gamma > 0$ (Gokcan, 2000). As mentioned by Gokcan (2000), this parameter is typically documented as negative in financial studies.

However, even if there are misspecifications in both the conditional mean and the dynamic behaviour of the conditional variances, GARCH-type models can still generate consistently robust forecasts for all short, medium, and long-term forecasts. As such, we skip the diagnostic tests for the estimated GARCH models and proceed to use the parameters calculated from the in-sample data to make forecasts for the out-of-sample period. This approach is also in line with previous studies such as Balaban et al. (2006), McMillan and Speight (2007).

4. Forecasting Performance Evaluation

The final stage is to evaluate the predictive power of estimated GARCH models Blair et al. (2001), Degiannakis (2004), McMillan and Speight (2007), this study employs the one-step-ahead rolling window which effectively rolls the sample forward one observation at a time (static forecast).

Previous studies have employed various performance measures which have their own merits and limitations. Hence, the researcher decides not to depend on a single measure to assess the forecasting performance of GARCH (1;1) type model. Instead, the researcher incorporates two main approaches – the error statistics and the information content regression in the performance appraisal of the GARCH (1;1) type model. Each approach is equally weighted in the ranking of the model.

4.1. Error Measures

Following other studies such as Balaban et al. (2006), Guidi (2010), the predictive powers of the model in this study is determined by the use of most popular criterion which are mean absolute error (MAE), root mean squared error (RMSE) whilst the mean absolute percentage error (MAPE) and Theil U coefficient was not applied due to its complexity. Since we use different measures to rank the performance of the model, we expect some disagreements among these loss functions. These measures are calculated as:

$$MAE = \frac{1}{T} \sum_{t=1}^T |\hat{\sigma}_t^2 - \sigma_t^2| \dots \dots (5)$$

$$RMSE = \sqrt{\frac{1}{T} \sum_{t=1}^T (\hat{\sigma}_t^2 - \sigma_t^2)^2} \dots (6)$$

Where $\hat{\sigma}_t^2$ is the forecasted volatility; σ_t^2 is the actual volatility and T is the size of the forecasting period. According to Makridakis et al., (1998), MAE is estimated by averaging the absolute values of forecast errors. It has the advantage of being more interpretable and simple to understand. Unlike MAE, RMSE is based on squared errors, hence it penalises large errors more than small errors. On the other hand, due to its association with quadratic loss functions, RMSE is more sensitive to outliers than MAE and this might decrease its evaluation accuracy (Brooks, 2008). The forecasting performance of the model will be compared according to error statistics from these measures. The lower their statistics are, the more accurate models are in estimating the volatility (Brooks, 2008).

5. Findings and Analysis

5.1. Stationarity or Unit root test (Augmented Dickey Fuller)

The main idea of carrying unit root is to statistically verify the null hypothesis that the return time series under observation is non stationary or have a unit root. Given the summary results from E-Views below the conclusion postulated is to reject the stated null hypothesis and conclude that the return series is stationary. This is so because at level the absolute t statistic value of 13.92302 is greater than the absolute critical t value of 3.4396, 2.8648 and 2.5685 at a significance level of 1%, 5% and 10% respectively. However, the results support the non Stationarity null hypothesis of return series as from the first to the fourth differencing because the absolute T statistic values are less than the critical T values at significance levels of 1%, 5% and 10%. The full regression results are presented in the appendix section.

ADF Test Statistic	-13.92302	1% Critical Value*	-3.4396
		5% Critical Value	-2.8648
		10% Critical Value	-2.5685

Table 1: Summary of ADF Unit Root Test

5.2. Autocorrelation test

For the autocorrelation test by Ljung-Box Q-statistic, as explained by Brooks (2008), the computed Q-statistic value of 406.20 is greater than Chi-squared critical value of 10.856 at 1% significance level after employing 24 lags. Therefore, this suggests that the null hypothesis that all the ρ_k are zero or no autocorrelation will be rejected. These results show that there is serial correlation of observations under review. The presence of this autocorrelation suggests that non linear econometric models are better than linear models because of the violation of the general ordinary least squares method assumption of no autocorrelation.

5.3. ARIMA Process

As mentioned earlier on the main objective behind ARIMA process estimation is to compute the white noise error terms which are useful in GARCH modeling. The estimation results from E-Views are shown below;

$$X_t^2 = \delta_t^2 = 0.529707 \delta_{t-1}^2 \dots\dots\dots(7)$$

From the above equation it is clearly evidenced that current volatility is positively related to its previous volatility since coefficient of δ_{t-1}^2 is greater than zero. These empirical findings are in agreement with the previous theories which explain the relationship between previous and current volatility. Given the above scenario it is now possible to determine the white noise error terms as shown below;

$$\mu_t = \delta_t^2 - 0.529707 \delta_{t-1}^2 \dots\dots\dots(8)$$

The white noise error terms computed will now be used in testing the presence of heteroskedasticity in residuals. In addition to the above these residuals are also important in the framework of modeling conditional volatility using the GARCH technique.

5.4. The Arch Effect Test

The residual test method applied for testing the presence of heteroskedacity is the Arch LM. Empirical findings show Obs*R squared statistic value of 68.67189 against a critical Chi-squared value of 6.635, 3.841 and 2.705 at 1%, 5% and 10% significance level respectively. The conclusion which can be drawn is to reject the null hypothesis that there is no Arch effect up to order q in the residuals. This is so because it was empirically proven even if we increase the number of lags. Therefore, as indicated by these results there is presence of varying variances of white noise error terms. In other words, there is heteroskedasticity. Given the above conclusion, volatility on return series is approximated using the Arch-Garch technique rather than ordinary least squares method because of the violation of ordinary least squares method assumptions.

5.5. Model Estimation

5.5.1. Symmetric Garch (1.1): Conditional Variance model

The results were computed using the Maximum likelihood approach with the assistance of E-Views. Results obtained were as follows,

	Variance Equation			
C	2.00E-10	6.41E-12	31.14965	0.0000
ARCH (1)	0.480363	0.035372	13.58024	0.0000
GARCH (1)	0.686016	0.009646	71.12182	0.0000

Table 2: Summary of Garch (1.1): Conditional Variance model

The three coefficients in the variance equation are listed as C, the intercept; ARCH (1), the first lag of the squared error term (μ_{t-1}^2); and GARCH (1), the first lag of the conditional variance (δ_{t-1}^2).

The Garch Variance equation will be;

$$\delta_t^2 = 0.000000002 + 0.480363 \mu_{t-1}^2 + 0.686016 \delta_{t-1}^2 \dots\dots\dots(9)$$

The results above show that the squared lagged residuals and previous stock return volatility have a positive impact on current volatility as supported by the coefficients of μ_{t-1}^2 and δ_{t-1}^2 which are greater than zero. The constant is approximately equal to zero;

Error of 0.0000836 Garch (1.1) model. The error measures from Egarch were 0.000272 and 0.0000492 for Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) respectively. EGarch (1;1) seems to be a good volatility forecasting model for Zimbabwe stock Exchange since the Error Statistic Measures are very small as compared to error statistic measures from Garch (1;1). In other words, forecasting errors are minimized when applying asymmetric model, EGARCH (1;1). Therefore, investors, portfolio managers and brokers just to mention a few may predict the price of financial instruments with certainty.

5.7. Information Content Evaluation

5.7.1. Information Criteria

Given the two models above (symmetric and asymmetric), it is vital to determine the best performing model according to two information criteria as mentioned in the methodology section. That is the Akaike Information criteria (AIC) and Schwarz's Bayesian Information Criteria (SBIC)

	Garch (1.1)	EGarch (1.1)
AIC	-16.99641	-17.04945
SBIC	-16.97199	-17.02014

Table 4: Summary of model comparison using information criteria

Using the information content criteria EGarch (1.1) rather than Garch (1.1) seems to be a best performing model since it minimizes both the AIC and BIC with values of -17.04945 and -17.02014 respectively. This shows that basing the rankings only on AIC and SBIC the EGARCH (1;1) seems to be a better model for both in-sample and out-of sample forecasting.

5.8. Regression Based Approach

As mentioned above, besides the error statistics and information criteria, this study also employs the regression-based evaluation as suggested by Mincer and Zarnowitz (1969). This study uses squared log returns as a proxy for the out-of-sample volatility which will be regressed on the forecasted variance from GARCH (1;1) and EGARCH (1;1) model with the ordinary least squares estimation. The validity of the model adopted is given by the R^2 from the regression results. Besides, this study also assesses whether the forecasts have any informative contents by testing the hypothesis that the coefficient β is significantly non zero.

	Garch (1.1)	EGarch (1.1)
R-squared	0.840276	0.906526
Coefficient of forecasted volatility ($\hat{\sigma}_t^2$)	2.584954	1.292487

Table 5: Summary of regression results

This study starts by assessing whether the forecasting models discussed have any informative contents by testing the hypothesis that the coefficient β is significantly non zero. The results from GARCH (1;1) and EGARCH (1;1) have coefficient of forecasted volatility which is not equal to zero. The non zero coefficient of forecasted volatility implies that current volatility and future volatility are positively related, this is so because rational investors use the current scenario to peek into the future. Therefore, the conclusion is to accept the stated null hypothesis and conclude that, both models have information content. However, basing model ranking with the stated coefficient β might not be necessary since both models proved to be good forecasting models. As a result, there is need to employ R-squared condition for determining goodness of fit of the model.

The results above show that the EGarch (1;1) is a better volatility forecasting model as compared to Garch (1;1). The coefficient of determination R-squared will be used to evaluate goodness of fit of the model. From these empirical findings, a high R-squared of 0.906526 from Egarch (1;1) which is greater than R-squared of 0.840276 from Garch (1;1), this suggests that about 91% change in current volatility is due to changes future volatility whereas the remainder of about 9% is due to other factors from the asymmetric Garch (1,1) model, (EGarch). On the other side about 84% change in present volatility is due to changes in future volatility, the shortfall of 16% variation in current volatility is due other factors not mentioned in the model. Given the above analysis it is clear that EGARCH (1;1) rather than GARCH (1;1) is a better volatility forecasting model as it captures the impact of shocks on stock returns.

6. Conclusion

Following the obtained empirical results, the researcher therefore recommends portfolio managers, brokers and investors in particular to use Maximum likelihood methods which are used to estimate the parameters from the historical data in Garch related models whenever modelling conditional variance or volatility of asset returns since financial time series data does not assume the normality assumption, and it exhibits the Stationarity characteristic and the presence of non constant variance. The main reason for recommending these models is that they involve using an iterative procedure to determine the parameter values that maximize the chance or likelihood that the historical data will occur.

The other recommendation is to use high order frequency such as daily data in order to get accurate and reliable volatility results. However, the researcher also recommends investors, portfolio managers and brokers to use intra-day data though it is difficult to get.

Due to large volatility in some of the capital markets, investors in these markets are likely to be worse-off. Therefore, it is recommended that under such conditions, expected returns must be raised. Strategies need to be designed toward reaping abnormal returns by exploiting information and actions that enhance inefficiency in stock markets. Firms and individuals should be encouraged to buy or sell securities outside their face values, as a means of encouraging business or economic activities in the economy in question.

6.1. Suggestion for Future Studies

Further studies should consider the general extensions of Garch models, in particular symmetric and asymmetric Garch (p; q) rather than symmetric and asymmetric Garch (1;1) model. This general extension is helpful because such higher order-models are often useful when long span of data is used. Therefore, with additional lags such models allow both fast and slow decay of information.

Since the choice of goodness-of-fit of volatility estimation and best-performing forecast models is still an interesting and open question, alternative GARCH

specifications as well as other simpler or more sophisticated approaches maybe conducted to give the systematically finding of best models.

Another suggestion is that further studies may employ multivariate models such as BEKK or Dynamic Conditional Correlation Multivariate model to analyze the time-varying correlation of Zimbabwe stock market with the other African stock markets in particular and international stock markets in general. The stated models examine the volatility spillovers and co variances between these markets' return series. Findings of those researches may give good indications to forecast volatility of Zimbabwe stock market.

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