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Assessing Financial Risk using Value-At-Risk from the perspective of a third world economy, Zimbabwe's Forex Market

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Abstract The Global Financial Crisis of 2008 exposed the problems of financial risk estimations in the forex sector and the negative impact on developing countries. In this paper, the performance of the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) family models is used to assess and compare the estimation of Value at Risk (VaR). The study is based on three major currencies that are used in Zimbabwe's multiple-currency regime against the USD. The three exchange rates considered are, the ZAR/USD, the EUR/USD, and the GBP/USD. Three univariate types of GARCH models, with seven error distributions (the normal, skewed-normal, Student's t, skewed-Student's t, generalized error distribution (GED), skewed-GED, and the generalized hyperbolic (GHYP) distribution) are applied to the three currency indices to ascertain the best VaR estimation method. Evaluation tests, namely the Kupiec's test and Christoffersen's test are used to assess the quality of the VaR performance. The GARCH (1, 1) with generalized error distribution produced relatively more accurate computations on the VaR for EUR/USD and ZAR/USD at both 99% levels of significance, while the backtests results for GBP/USD suggested that the GJR-GARCH(1,1) model with skewed t-distributed errors is the optimal outcome. While the student's t-distributed error model is mostly recommended by many findings in literature, this study suggests that GED produces superior resultsin the case of the Zimbabwe forex market. In a third world economy with a multi-currency regime, like Zimbabwe, findings suggest that the GARCH (1,1) with GED errors is the optimal model for computing VaR and making other deductions on the capital required, and in selecting the currency to use for preservationof monetary value. Based on volatility persistence coefficient, this study recommends to risk practitioners, keeping savings in GBP than in any other currencies under study in the case of the Zimbabwe forex market.

Keywords Value at Risk, GARCH Model, Financial Risk, Back testing, multi-currency

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1. Introduction

The growth in trading activities and events in the financial markets underscore the need for market players to develop/use reliable risk measurement techniques. One technique commonly used and recommended by researchers/practitioners is the Value at Risk (VaR) model. VaR is a statistic that measures the riskiness of financial entities or portfolios of assets. It is defined as the maximum monetary (say dollars) amount expected to be lost over a given time horizon, at a pre-defined statistical confidence level. Traditional VaR estimation methods have shown several limitations. Traditional approaches include Historical Simulation (HS), the Delta-Normal, and unconditional approaches. The Delta-Normal method always assumes joint normality of the financial returns. The unconditional approach assumes homoscedasticity, which is constant volatility over the period under study. However, in reality these assumptions do not always hold. The basic driving principle of the historical simulation method is its assumption that the VaR forecasts can be based on historical data.

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1.1. GARCH models

The major drawback of the assumption of constant volatility is its inability to capture important features of financial behavior, which are clustering, leptokurtosis, and nonlinearity. [1] introduced the Autoregressive Conditional Heteroskedasticity (ARCH) models. [2] proposed the generalization of the ARCH process, calling it the GARCH model. The ARCH and GARCH models are capable of capturing several major properties of a financial time series that are mentioned above. Many research findings, as shall be discussed under the literature review, show that the GARCH family models outperform traditional VaR methodologies and are more accurate in VaR predictions.

1.2. Statement of the problem

The decision by banks and financial market players on how much capital to maintain as a cushion against losses must be proportional to the riskiness of their portfolios. There is a need to correctly and effectively develop a model that better mimics the risk adopted by the firm. A lower estimate of VaR leads to lower/insufficient capital maintained by the bank. VaR assesses cumulative risks from aggregated positions held by different trading desks and departments within banks or other institutions. Using the information provided by a VaR model, investors can determine whether they have sufficient capital reserves in place to cover losses or whether higher than acceptable risks require them to reduce concentrated holding positions. The absence of a standard protocol for the statistics to be used in determining the portfolio risk may lead to underestimation or overestimation of the magnitude of the portfolio or the firms' potential risk. For example, statistics collected arbitrarily from a period of low volatility may underestimate the potential risk. Furthermore, the risk might be underestimated in using the Normal distribution probabilities, which to a larger extent do not account for extremes or outliers. This study seeks to use the GARCH based models, since they allow the variance or standard deviation to be non-constant, to compute VaR and apply backtesting to ascertain empirically, the best VaR model for univariate data in Zimbabwe's major foreign currency counters, under the multi-currency regime. Risk is measured from the perspective of a third world economy holding the currencies: ZAR, GBP, and EUR. Trading in these currencies is done via the USD and therefore the exchange rates against the USD becomes very important.

1.3. Objectives of the study

The objectives of this paper are: firstly, to fit univariate GARCH family models under different error distributions and define the best method for VaR estimation using the above-mentioned forex data. Secondly to apply backtesting techniques invalidating the fitted VaR models in the forex exchange market in Zimbabwe. Risk in the forex market is then perceived from the perspective of such a developing country.

The contribution of this study is in combining GARCH and VaR techniques in modeling financial risk in the forex market in a third world economy, Zimbabwe. This study is organized as follows: Section 2 presents a review of the literature, section 3 presents the research models, section 4 is on Data Analysis, Presentation of Results, and Discussion, section 5 gives a summary of the findings and areas of further study

2. Review of Literature

[3] assessed the performance of the RiskMetrics method, as well as the GARCH and Integrated GARCH (IGARCH) models in VaR forecasting of a stock exchange index in the Serbian financial market. Their findings were that the GARCH models combined with extreme value theory (the peaks-over-threshold method) performed better than the RiskMetrics method and the IGARCH model. [4] came to the conclusion that the methodologies of extreme value theory are better than the GARCH model regarding the calculation of VaR, based on their analysis of stock exchange indices in Central and Eastern European countries (Bulgaria, Czech Republic, Hungary, Croatia, Romania, and Serbia), but they suggested the use of both approaches for an improved market risk measurement. [5] concluded that the most adequate GARCH family of models for estimating volatility in the Macedonian stock market is the Exponential GARCH (EGARCH) model with innovations that follow a Student's t-distribution. These findings have important implications regarding VaR estimation in volatile conditions that have to be addressed

by investors in developing capital markets. [6] implemented GARCH family models that involve time-varying volatility and heavy tails to the empirical distribution of returns, in Croatia, Czech, Hungary, Romania, and Serbia. Their results showed that the GARCH models with a t-distribution of residuals in most analyzed cases, give a better VaR estimation than GARCH models with Normal errors in the case of a 99% confidence level, while the opposite is true in the case of a 95% confidence level. The backtesting results for the crisis period showed that GARCH models with a Student's t distribution of residuals provide better VaR estimates when compared with GARCH models with a Normal distribution, historical simulations, or the RiskMetrics methods.

[7] studied the shock persistence and asymmetry in Nigerian stock market by using monthly stock returns for the period from January 1985 to December 2014.They partitioned the study period into pre-structural break period and after break period having identified breakpoints in the series. Their result from the basic GARCH model showed higher shock persistence during pre-break sub-period than the post break sub-period. No evidence of asymmetry or leverage effect was found in the asymmetric GARCH model with or without incorporating the break-points in Nigerian stock market.

[8], considered the adequacy of the GARCH model used in measuring financial risk in the Montenegrin emerging market before and during the global financial crisis (January 2004–February 2014). Their backtesting results showed that none of the eight proposed models passed the Kupiec test with a 95% of confidence level, while only the ARMA (autoregressive moving average model) (1,2)–N GARCH model did not pass the Kupiec test with a confidence level of 99%. The results of the Christoffersen test revealed three models (ARMA(1,2)–TS GARCH(1,1) with a Student-t distribution of residuals, the ARMA(1,2)–T GARCH(1,1) model with a Student-t distribution of residuals, and ARMA(1,2)–EGARCH(1,1) with a re-parameterized unbounded Johnson distribution [JSU] distribution of residuals) passed the joint Christoffersen test with a 95% confidence level, and none of the analyzed models passed the Pearson's Q test, whether with 90%, 95% or 99%.

The aim of this study is to assess the efficacy of GARCH based Value at Risk in the context of a third world economy, Zimbabwe, under a multi-currency regime. To the best of our knowledge, a study of this nature has never been carried out in a third world economy under a multi-currency regime.

3. Research Models

According to [9], the behaviour of the financial time series follows these three statistical properties which are volatility clusters, leptokurtosis, and nonlinear dependence. Volatility clustering is when a period of large returns is followed by a period of small returns ([10]). A plausible explanation for this phenomenon, which seems to be an almost universal feature of asset return series in finance, is that the information arrivals, which drive price changes themselves, occur in bunches rather than being evenly spaced over time ([11]). Leptokurtosis is the tendency for financial asset returns to have distributions that exhibit fat tails and excess peaks from the mean. It is responsible for extreme returns and may be driven by the arrival of unexpected news. Nonlinear dependence is the correlation between multivariate financial data that is stock indices during the financial crisis, are likely to move together in the same direction relevant to some market conditions ([9]).

3.1. Auto-Regressive Conditional Heteroskedasticity (ARCH) Models

[1] described Auto-Regressive Conditional Heteroskedasticity, as "…mean zero, serially uncorrelated processes with non-constant variances conditional on the past, but constant unconditional variances". Engle proposed a decomposition of ϵ_t as:

$$\epsilon_t = \sigma_t z_t, \tag{1}$$

where ϵ_t is a random variable representing a financial return at time t, with a zero mean and variance conditional on the past time series $\epsilon_1, ..., \epsilon_{t-1}$. z_t is a sequence of independent, identically distributed random variable at time t, with a zero mean and a unit variance.

The mean equation model for the returns is:

$$\varepsilon_t = \mu_t + \epsilon_t, \tag{2}$$

where it can be established that $\mu_t = 0$, and ϵ_t is an error term. The distribution of $z_t$is assumed to be leptokurtic ([12]), and the conditional variance of the ARCH model of order is modelled as:

$$\sigma_t^2 = w + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2, \tag{3}$$

where $w > 0$, $\alpha_i > 0$. However, in many of the financial time series applications with the ARCH models, a high ARCH order has to be selected to catch the dynamics of the conditional variance of the data. The high order of the model of course implies that many parameters have to be estimated and this is also a difficult task. Another practical challenge is that the high order of the model estimation will often lead to the violation of the non-negativity constraints on the parameters that are needed to ensure that the conditional variance is always positive.

3.2. *Generalised Auto-Regressive Conditional Heteroscedasticity (GARCH) Models*

[2] proposed the Generalised ARCH (GARCH) models, as a natural solution of the high ARCH orders problem. The proposed GARCH model is based on an infinite ARCH and reduces the number of parameters that needs to be estimated from infinite number to just a few parameters. The main principle of modelling time series using a GARCH model is that, a large movement in assets' behaviour in a given period increases the variance of the movements in the following periods (volatility clustering).

$$\varepsilon_t = \sigma_t z_t \tag{4}$$

Then GARCH (q,p)

$$\sigma_t^2 = w + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-1}^2, \tag{5}$$

where q is the order of ε_{t-1}^2 and p the order of σ_{t-1}^2. The necessary conditions to impose, are:$w > 0$, $\alpha_i > 0$, $\beta_j > 0$, $sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1$, to get a positive and stationary conditional variance. The process ε_t is covariance stationary and its unconditional variance is equal to:

$$\sigma^2 = \frac{w}{1 - sum_{i=1}^{q} \alpha_i - \sum_{j=1}^{p} \beta_j}. \tag{6}$$

In general a GARCH(1,1) model will be sufficient to capture the volatility clustering in the data, and rarely is any higher order model estimated or even entertained in the academic finance literature([11]). A GARCH (1,1) model is written as:

$$\sigma_t^2 = w + \alpha_i \varepsilon_{t-1}^2 + \beta_j \sigma_{t-1}^2, \tag{7}$$

where: ε_t are the returns with zero mean and unit variance, and w, α_1, β_1,– are model coefficients ($w > 0$, $\alpha_1 > 0$, $\beta_1 > 0$, and $\alpha_1 + \beta_1 < 1$), and $\frac{w}{1-\alpha_1-\beta_1}$, σ^2 is the GARCH(1,1), unconditional variance of ε_t.

3.3. *Extensions to the Basic GARCH Model*

Since the development of the GARCH model, a huge number of extensions and variants have been proposed. A couple of the most important were investigated and a comprehensive survey was reported by [13]. Many of the extensions to the GARCH model have been suggested as a consequence of perceived problems with standard GARCH(q, p) models ([11]). First, the non-negativity conditions may be violated by the estimated model. The only way to avoid this for sure, would be to place artificial constraints on the model coefficients in order to force them to be non-negative. Second, GARCH models cannot account for leverage effects, although they can account for volatility clustering and leptokurtosis in a series. Finally, the model does not allow for any direct feedback between the conditional variance and the conditional mean.

3.4. Exponential GARCH (EGARCH) Models

[10] introduced the Exponential GARCH model and noted the model can address the main limitations of the simple GARCH model which are negative correlation between ε_t and ε_{t-1} which is excluded by the GARCH model assumption. According to [12], the EGARCH (q, p) is given by:

$$log(\sigma_t^2) = w + \sum_{i=1}^{q}[\alpha_i\varepsilon_{t-i} + \lambda_i(\alpha_i|\varepsilon_{t-i}| + E|\varepsilon_{t-i}|] + \sum_{j=1}^{p}\beta_j log(\sigma_{t-1}^2). \tag{8}$$

An EGARCH (1, 1) can be expressed as:

$$log(\sigma_t^2) = w + [\alpha_1\varepsilon_{t-1} + \lambda_1(\alpha_1|\varepsilon_{t-1}| + E|\varepsilon_{t-1}|] + \beta_1 log(\sigma_{t-1}^2). \tag{9}$$

Where ε_t are returns with zero mean and unit variance and $w,$, α_1, β_1, λ_1- are model coefficients. $\alpha_1\varepsilon_t$ has a sign or asymmetry effect. Since the logarithm is always positive, positivity constraints are not necessary in the EGARCH model. Asymmetry model depends on the coefficient α_1. For instance, when $\alpha_1 < 0$, $log(\sigma_t^2)$ would be bigger than the mean w if $\varepsilon_{t-1} < 0$ and it would be smaller if $\varepsilon_t > 0$.. This means that when $\alpha_1 < 0$ negative news has greater effects than positive news. On the other hand, when $\alpha_1 > 0$ positive news have larger effects on the conditional variance than negative news. This shows typical asymmetry of the financial time series. The meaning of $E|\varepsilon_{t-1}|$ depends on the error distribution.

[14] showed that: $E|\varepsilon_{t-1}| = \sqrt{\frac{2}{\pi}}$, when the error distribution is Normal and $E|\varepsilon_{t-1}| = \frac{2\sqrt{\nu-2}\Gamma(\frac{\nu+1}{2})}{\sqrt{\pi}(\nu-1)\Gamma\frac{\nu}{2}}$,

3.5. GJR-GARCH Models

The Threshold GARCH model was proposed by [15] and the model reveals and takes into account the asymmetry property of financial data in obtaining the conditional Heteroskedasticity (see Glosten, Jagannathan and Runkle, 1993). The model is commonly known as GJR-GARCH. The GJR-GARCH (q, p) model is as follows:

$$\sigma_t^2 = w + \sum_{i=1}^{q}(\alpha_i + \lambda_i I_{t-i})\varepsilon_{t-1}^2 + \sum_{j=1}^{p}\beta_j\sigma_{t-1}^2, \tag{10}$$

where I_{t-i} is an indicator function $I_{t-i} = \begin{cases} 1 & \text{if } \varepsilon_{t-1} < 0, \\ 0 & \text{otherwise.} \end{cases}$

Empirical results show that the effects of negative shocks are more significant than that of positive on the conditional variance and the GJR-GARCH model is able to reflect this specific feature of financial data.

A GJR-GARCH (1,1) model is given as:

$$\sigma_t^2 = w + (\alpha_i + \lambda_1 I_{t-1})\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2, \tag{11}$$

$w,$, α_1, β_1, λ_1- are model coefficients, the conditions for non-negativity are: $w > 0$, $\alpha_1 > 0$, $\beta_1 \geq 0$, and $\alpha_1 + \lambda_1 \geq 0$. That is, the model is still admissible, even if $\lambda_1 < 0$ provided that, $\alpha_1 + \lambda_1 \geq 0$.

3.6. Error Distributions

Financial time series data often reveals a fat-tail property. This has led to researchers considering alternative distribution assumptions for error terms to the Normal distribution. Although the Normal distribution is still widely used as an error distribution in GARCH models, more complex distributions such as skewed-normal, Student's t, skewed-Student's t, generalized error distribution (GED), skewed-GED and the generalized hyperbolic (GHYP) distribution.. The STD in GARCH models was initially popularized by [2]. [10] showed the usefulness of the GED in modeling financial time series with GARCH models.

One of the objectives of this research is to ascertain which error distribution, gives a better estimation of the VaR for the univariate GARCH family of models in the case of the exchange rates data. In this research, seven distributions for error terms shall be employed, namely: the normal, skewed-normal, Student's t, skewed-Student's t, generalized error distribution (GED), skewed-GED, and the generalized hyperbolic (GHYP) distribution.

3.7. Back testing Value at Risk Models

After applying different GARCH family models in the computation of VaR, there is a need to assess the predictive accuracy of each model using different statistical tests. There are several evaluation techniques that are known for model checking, like residuals analysis, testing for Normality in distribution, etc. In this paper, out-of-sample VaR estimates are used to check the risk forecasts. In the sample, VaR estimates are obtained based on the previousyears' observations and are compared with the actual data. In this research, the Kupiec's test and Christoffersen's test are used.

3.8. The Kupiec's Test

Assume that the probability that the loss L exceeds VaR_p is $(1-p)$:

$$P(L \geq VaR_p) \leq 1-p. \tag{12}$$

A violation is when the actual loss exceeds the VaR forecast.

The number of exceeds over time follow a binomial distribution. The Kupiec's test helps to determine the consistency of these violations at a given confidence level. If the number of the actual exceeds significantly differ from the expected, then the risk model's adequacy is unsatisfactory ([9]). To do the test we need $E =$ total actual violations, $N =$ total observations and $p =$ the VaR probability level. Assuming $E \sim Bin(N,p)$ the null hypothesis is:

$H_0 : p = p_0$ that is $p_0 = 0.01$ or 0.05 where $p = \frac{E}{N}$. The test is to ascertain whether E is considerably different from the expected number of violation $sp \times N$. [16] proposed the use of the likelihood ratio statistic LR to test the violation rate.

$$LR = 2log\left[\frac{(1-\frac{E}{N})^{N-E}(\frac{E}{N})^{E}}{(1-p_0)^{N-E}p_0^{E}}\right] \sim \chi_1^2 \tag{13}$$

3.9. Christoffersen's conditional Test

[17] proposed a test based on the conditional coverage. This test determines whether a violation occurred today is conditionally dependent on the yesterday's result. The steps involved in carrying out this test as outlined by [9] are: Firstly compute the following transitional probabilities:

$$p_{ij} = Pr(m_t = i | m_{t-1} = j), \tag{14}$$

Where i and j are either 0 or 1 and m_t means whether a VaR exceedance occurs at time t.

$$\Pi_1 = \begin{bmatrix} 1-p_{01} & p_{01} \\ 1-p_{11} & p_{11} \end{bmatrix} \begin{cases} 1 = \text{no exceeds}, \\ 0 = \text{no exceeds}. \end{cases} \tag{15}$$

Where p_{01} is the probability of a violation today when there was no violation yesterday and p_{11} is the probability of two consecutive days of violations. Under the null hypothesis H_0, assume that all the violations are independent, that is $H_0 : p_{01} = p_{11} = p$.

The transition matrix is:

$$\hat{\Pi} = \begin{bmatrix} 1-\hat{p} & \hat{p} \\ 1-\hat{p} & \hat{p} \end{bmatrix}, \tag{16}$$

$$\hat{p} = \frac{\nu_{01} + \nu_{11}}{+\nu_{00} + \nu_{10} + \nu_{01}\nu_{11}} \tag{17}$$

where ν_{ij} number of cases where j follows $i, i = 1$ means violation and $i = 0$ means no violation. The Likelihood function is:

$$L_0 = (1-\hat{p})^{\nu_{00}+\nu_{10}} \times \hat{p}^{\nu_{01}+\nu_{11}} \tag{18}$$

4. Data Analysis and Discussion

Quantitative data was collected and modelled so as to achieve the set. Data was obtained from the finance sector website (www.investing.com/currencies).The currencies considered are the South African Rand (ZAR), the European Union currency EURO (EUR), and the British Pound (GBP). The exchange rates are considered with respect to the USD.The data was analysed in an R-programming environment. The daily exchange rates considered were from 1 January 2010 to 31 December 2018. This is the period where the local currency (the Zimbabwean Dollar) was replaced by multi-currency system with the USD being the valuation currency. The currencies were considered because of the volume of exports that were destined to the countries that own the currencies.

4.1. Data Presentation and Analysis Methods

The log returns were calculated and used to do the modelling. The formula used is:

$$\log\left[\frac{p_t}{p_{t-1}}\right], \tag{19}$$

where p_t and p_{t-1} are today and yesterday's closing values of daily prices (exchange rates)respectively. Closing prices of the currency rates are considered for the analysis. Table 1 provides summary statistics of the daily log

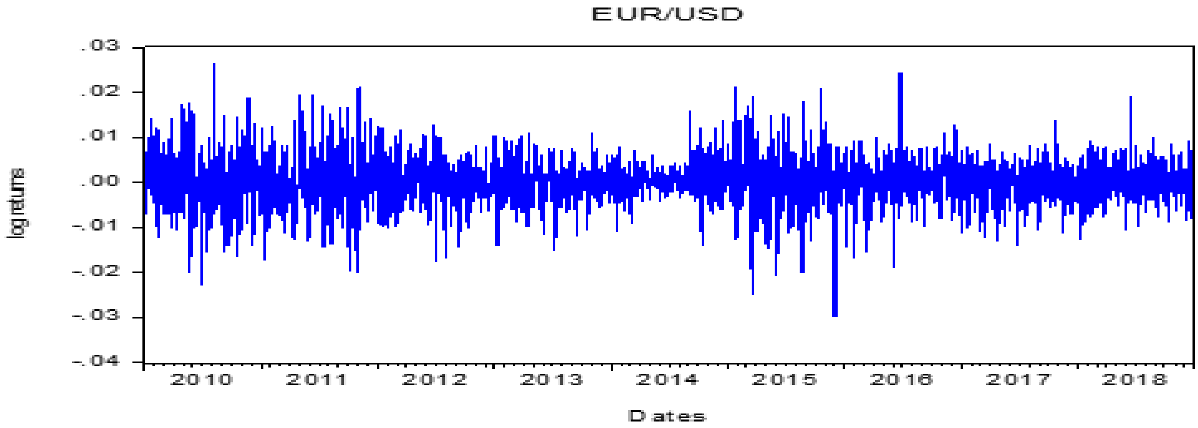
Table 1. Descriptive Statistics

	EUR/USD	GBP/USD	ZAR/USD
Mean	9.95×10^{-5}	9.92×10^{-5}	2.67×10^{-4}
Median	0	0	-3.85×10^{-5}
Maximum	0.026398	0.084006	0.067143
Minimum	-0.029953	-0.029962	-0.049902
Std. Dev.	0.00573	0.005529	0.009723
Skewness	0.033719	1.519106	0.334327
Kurtosis	4.656914	26.65675	5.146971
Jarque-Bera	268.8039	55607.31	494.2809
Probability	0	0	0
Sum	0.233489	0.232671	0.626032
Sum Sq. Dev.	0.076993	0.071678	0.221706
Observations	2346	2346	2346

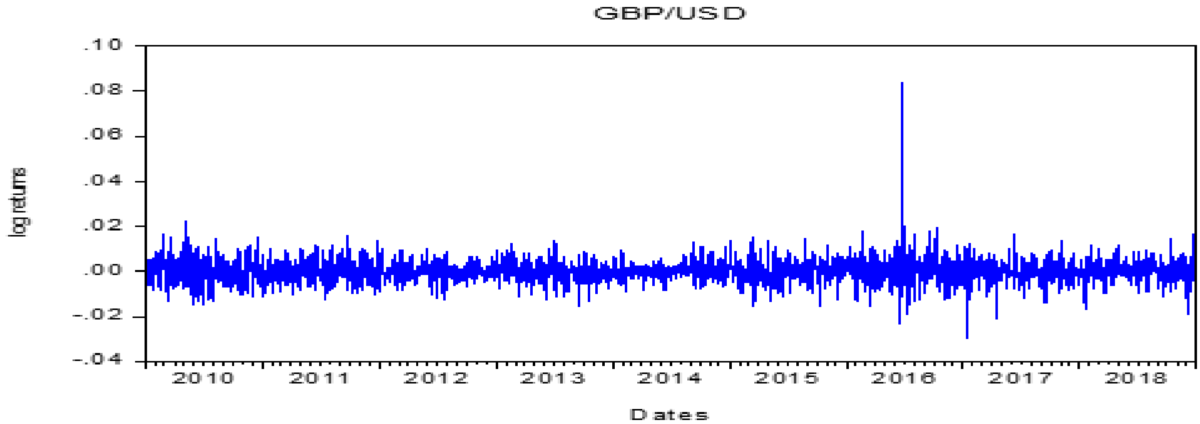
returns, for the period of January 1st of 2010 to December 31st of 2018, as well as the Jarque-Bera statistic for testing Normality in distribution. In all cases, the null hypothesis of Normality in distribution is rejected at Normal value levels of significance, as there is evidence of significant excess kurtosis and positive skewness.

4.2. Characteristics of the returns series

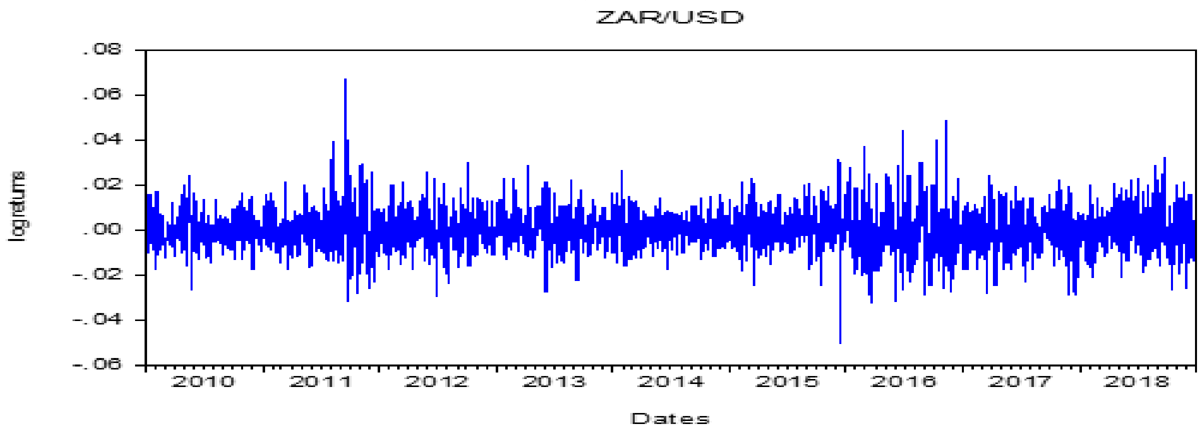
The following graphs show a Continuously Compounded Daily Returns of the 3 currencies.



(a)



(b)



(c)

Figure 1. Characteristics of the returns series (a) EURO/USD returns (b) GBP/USD return (c)ZAR/USD return.

The Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) graphs confirmed the mean equation as the model $\varepsilon_t = \mu_t + \epsilon_t$ with $\mu_t = 0$. There is evidence of volatility clustering (high volatility is followed by high volatility and low volatility is followed by low volatility) is clearly visible in all the three currency exchange rates graphs, therefore, the GARCH diffusion model may be appropriate for modelling the data.

4.3. Parameter Estimation

Table 3 shows a summary of the estimated GARCH(1,1) parameters for the EUR/USD exchange rate under seven error distributions. (*See the appendix for other models) The model's parameters are significant at 1% level except for omega (and some parameters under skewed GED and GHYP. The Ljung-Box test statistic values show that there is no evidence of autocorrelation in the model residuals as p-values of both the squared residuals and standardized squared residuals at all lags (Lag 1, Lag 2, and Lag 4) are all above 0.05. There is no evidence of dependencies in the standardized series as indicated by the ARCH LM test statistic values since all p-values (at Lag 3, Lag 5, and Lag 7) are above 0.05.

Table 4 shows a summary of the estimated EGARCH(1,1) parameters for the GBP/USD exchange rate under seven error distributions. (*See the appendix for other models) The model's parameters are significant at a 1% level except for omega (and under normal and skewed normal error distributions. The Ljung-Box test statistic values show that there is no evidence of autocorrelation in the model weighted residuals as p-values of both the squared residuals lags (Lag 1, Lag 2, and Lag 4) which are all above 0.05, however, the weighted standardized squared residuals show some evidence of autocorrelation. There is no evidence of dependencies in the standardized series as indicated by the ARCH LM test statistic values since all p-values (at Lag 3, and Lag 7) are above 0.05. However, at lag 5 there are signals of dependencies in the standardized series, which makes the model undesirable.

Table 5 gives a summary of estimated GJR-GARCH(1,1) parameters for the ZAR/USD exchange rate under seven error distributions. (*See the appendix for other models) The model's parameters are significant at a 1% level except for omega (and under normal and skewed normal error distributions. The Ljung-Box test statistic values show that there is no evidence of autocorrelation in the model weighted residuals as p-values of both the squared residuals lags (Lag 1, Lag 2, and Lag 4) which are all above 0.05, however, the weighted standardized squared residuals show some evidence of autocorrelation. There is no evidence of dependencies in the standardized series as indicated by the ARCH LM test statistic values since all p-values (at Lag 3, and Lag 7) are above 0.05. However, at lag 5 there are signals of dependencies in the standardized series, which makes the model undesirable.

The sum of ARCH term and GARCH term is greater than unity, i.e., $(\alpha_1 + \beta_1)$ helps us determine whether the conditional variance is stable and predictable and stationarity. The cases where $(\alpha_1 + \beta_1 > 1)$ indicates over persistence of shocks in each currency. The EUR/USD and ZAR/USD show over persistence, meaning that they are explosive and shocks lasts longer than GBP.

Table 2. Summary of volatility persistence for each currency under different error distributions

Variables	Model	Volatility						
		Normal	sNormal	STD	SSTD	GED	SGED	GHYP
EUR/USD	GARCH(1,1)	0.9974	0.9972	0.9986	0.9980	0.9975	0.9978	0.9989
	eGARCH(1,1)	1.0233	1.0232	1.0202	1.0201	1.0219	1.0219	1.0203
	GJR-GARCH(1,1)	1.0096	1.0038	1.0098	1.0096	1.0095	1.0096	1.010
GBP/USD	GARCH(1,1)	0.9910	0.9924	0.9941	0.9937	0.9944	0.9935	0.9946
	eGARCH(1,1)	0.9756	0.9787	1.0260	1.0262	1.0089	1.0103	1.0263
	GJR-GARCH(1,1)	0.9855	0.9895	1.0049	1.0058	1.0005	0.9988	1.0043
ZAR/USD	GARCH(1,1)	0.9853	0.9872	0.9848	0.9871	0.9848	0.9869	0.9871
	eGARCH(1,1)	1.0374	1.0382	1.0369	1.0368	1.0367	1.0367	1.0720
	GJR-GARCH(1,1)	1.0177	1.0180	1.0170	1.0167	1.0171	1.0178	1.0166

Table 3. **GARCH(1,1) model for EUR/USD exchange rate**

	Volatility Persistence						
Variables	Normal	Skewed Normal	STD	Skewed STD	GED	Skewed GED	GHYP
ω	Estim p- 0.0000 (0.846)	Estim p- 0.0000 (0.861)	Estim p- 0.0000 (0.953)	Estim p- 0.0000 (0.980)	Estim p- 0.0000 (0.954)	Estim p- 0.0000 (0.998)	Estim p- 0.0000 (0.971)
α_1	0.0263 (0.000)	0.0262 (0.000)	0.0309 (0.000)	0.0300 (0.0099)	0.0297 (0.0009)	0.0287 (0.0912)	0.0302 (0.0063)
β_1	0.9711 (0.000)	0.971 (0.000)	0.9677 (0.000)	0.968 (0.000)	0.9678 (0.000)	0.9691 (0.000)	0.9687 (0.000)
Shape			8.7139 (0.001)	8.6073 (0.000)		1.4891 (0.709)	0.2502 (0.934)
Skew	(0.000)	1.035	(0.000)	1.035 (0.000)	1.4944 0(0.000)	1.0413 (0.000)	0.5012 (0.912)
Ghlambda							-4.339 (0.002)
$\alpha_1 + \beta_1$	0.9974	0.9972	0.9986	0.9980	0.9975	0.9978	0.9989
Goodness of fit AIC BIC	-7.5937 -7.5864	-7.5935 -7.5837	-7.6210 -7.6111	-7.6208 -7.6085	-7.6166 -7.6068	-7.6168 -7.6045	-7.6195 -7.6047
Weighted Ljung-Box test on stdised res Lag[1]	Statistic (p-value) 1.152 (0.2832)	Statistic (p-value) 1.146 (0.2843)	Statistic (p-value) 1.008 (0.3154)	Statistic (p-value) 1.057 (0.3039)	Statistic (p-value) 0.9987 (0.3176)	Statistic (p-value) 1.068 (0.3015)	Statistic (p-value) 1.063 (0.3026)
Lag[2*(p+q)+(p+q)-1][2]	4.274 (0.4173)	1.269 (0.4187)	1.132 (0.4572)	1.185 (0.4420)	1.1158 (0.4622)	1.191 (0.4403)	1.192 (0.4398)
Lag[4*(p+q)+(p+q)-1][5]	2.193 (0.5736)	2.186 (0.5751)	2.029 (0.6117)	2.091 (0.5971)	2.0052 (0.6172)	2.094 (0.5964)	2.102 (0.5945)
Weighted Ljung-Box test on stdised res Lag[1]	Statistic (p-value) 0.1937 (0.6598)	Statistic (p-value) 0.1926 (0.6608)	Statistic (p-value) 0.0038 (0.9508)	Statistic (p-value) 0.01228 (0.9117)	Statistic (p-value) 0.03419 (0.8533)	Statistic (p-value) 0.04953 (0.8239)	Statistic (p-value) 0.008309 (0.9274)
Lag[2*(p+q)+(p+q)-1][5]	1.6474 (0.7036)	1.6496 (0.7031)	2.0110 (0.6158)	1.90848 (0.6402)	1.90002 (0.6422)	1.81430 (0.6629)	1.914001 (0.6389)
Lag[4*(p+q)+(p+q)-1][9]	3.1172 (0.7395)	3.1213 (0.7388)	3.5533 (0.6652)	3.41421 (0.6891)	3.43921 (0.6848)	3.31577 (0.7059)	3.412750 (0.6893)
Weighted ARCH LM Tests ARCH Lag[3]	Statistic (p-value) 0.3287 (0.5664)	Statistic (p-value) 0.3315 (0.5648)	Statistic (p-value) 0.6671 (0.4141)	Statistic (p-value) 0.6027 (0.4376)	Statistic (p-value) 0.574 (0.4487)	Statistic (p-value) 0.5155 (0.4728)	Statistic (p-value) 0.6125 (0.4339)
ARCH Lag[5]	1.4932 (0.5949)	1.4901 (0.5941)	1.6184 (0.5617)	1.5626 (0.5760)	1.616 (0.5623)	1.5565 (0.5776)	1.5507 (0.5791)
ARCH Lag[7]	2.2921 (0.6556)	2.2983 (0.6543)	2.5860 (0.5949)	2.4861 (0.6153)	2.551 (0.6020)	2.4476 (0.6232)	2.4732 (0.6180)

4.4. Back testing of VaR

The Estimation of VaR is from 2 January 2010 to 31 December 2018, using the fitted GARCH models. This is then followed by evaluating the performance of each GARCH based VaR computed using Back Testing techniques.

Table 4. **EGARCH(1,1) for GBP/USD exchange rate**

	eGARCH(1,1)						
Variables	Normal	Skewed	STD	Skewed	GED	Skewed	GHYP
ω	Estim p- -0.2194 (0.0000)	Estim p- -0.2065 (0.0000)	Estim p- -0.0619 (0.0e+00)	Estim p- 0.0597 (0.0e+00)	Estim p- -0.1043 (0.0000)	Estim p- -0.0967 (0.0000)	Estim p- -0.0587 (0.0000)
α_1	-0.0029 (0.7925)	-0.0010 (0.9238)		0.0320 (6.3e-05)	0.0187 (0.0728)	0.0194 (0.0557)	0.0318 (0.0001)
β_1	0.9785 (0.0000)	0.9797 (0.0000)	0.0318 (8.5e-05)	0.9944 (0.0e+00)	0.9902 (0.0000)	0.9909 (0.0000)	0.9945 (0.0000)
λ_1	0.1640 (0.0000)	0.1556 (0.0000)	0.9942 (0.0e+00)	0.0522 (0.0e+00)	0.0940 (0.0000)	0.0898 (0.0000)	0.0512 (0.0000)
Shape			0.0533 (0.0e+00)	7.5286 (0.0e+00)	1.3738 (0.0000)	1.3792 (0.0000)	0.250 (0.7011)
Skew		1.066 (0.0000)	7.4950 (0.0e+00)	1.0297 (0.0e+00)		1.035 (0.0000)	0.6438 (0.5214)
Ghlambda							-3.8208 (0.0000)
$\alpha_1 + \beta_1$	0.9756	0.9787	1.026	1.0262	1.0089	1.0103	1.0263
Goodness of fit AIC BIC	 -7.6759 -7.6661	 -7.6779 -7.6656	 -7.7392 -7.7269	 -7.7388 -7.7241	 -7.7234 -7.7111	 -7.7233 -7.7086	 -7.7382 -7.7210
Weighted Ljung-Box test on stdised res Lag[1]	Statistic (p-value) 1.512 (0.2188)	Statistic (p-value) 1.522 (0.2173)	Statistic (p-value) 1.262 (0.2613)	Statistic (p-value) 1.249 (0.2637)	Statistic (p-value) 1.510 (0.2192)	Statistic (p-value) 1.499 (0.2209)	Statistic (p-value) 1.240 (0.2654)
Lag[2*(p+q)+(p+q)-1][2]	1.517	1.526	1.277	1.265	1.510	1.499	1.256
Lag[4*(p+q)+(p+q)-1][5]	1.641	1.652	1.459	1.448	1.651	1.644	1.441
Weighted Ljung-Box test on stdised res sqd Lag[1]	Statistic (p-value) 0.5123 (0.4741)	Statistic (p-value) 0.735 (0.3913)	Statistic (p-value) 7.188 (0.0073)	Statistic (p-value) 7.319 (0.0068)	Statistic (p-value) 3.716 (0.0539)	Statistic (p-value) 4.050 (0.0442)	Statistic (p-value) 7.495 (0.0062)
Lag[2*(p+q)+(p+q)-1][5]	4.3554	4.625	10.672	10.789	7.669	7.998	10.965
Lag[4*(p+q)+(p+q)-1][9]	6.8878	7.218	13.241	13.351	10.462	10.796	13.530
Weighted ARCH LM Tests ARCH Lag[3] Statistic	Statistic (p-value) 1.937 (0.1640)	Statistic (p-value) 1.771 (0.1833)	Statistic (p-value) 0.2688 (0.6042)	Statistic (p-value) 0.2616 (0.609)	Statistic (p-value) 0.7116 (0.3989)	Statistic (p-value) 0.6648 (0.4149)	Statistic (p-value) 0.2561 (0.6128)
ARCH Lag[5]	7.072 (0.0335)	7.236 (0.0306)	6.9369 (0.0361)	6.9113 (0.0366)	7.7393 (0.0232)	7.7465 (0.0231)	6.9134 (0.0365)
ARCH Lag[7]	7.728 (0.0603)	7.897 (0.0553)	7.5936 (0.0645)	7.5680 (0.0654)	8.4122 (0.0425)	8.4206 (0.0423)	7.5734 (0.0652)

Tables 6, 7 and 8 show the VaR backtesting results for the three currency exchange rates understudy, the best model is the one with the highest p-value. Due to the discrepancies between the Kupiec and Christoffersen's tests results at different levels of significance, we then used the average p-values to select the optimal model for each exchange rate. For the EUR/USD rate, GARCH(1,1) with generalized error distribution is the optimal model, Whilst for GBP/USD and ZAR/USD, GJR-GARCH(1,1) with GED and GARCH (1,1) skewed STD are optimal models respectively.

Table 5. **GJR-GARCH(1,1), model for ZAR/USD exchange rates**

	Volatility Persistence						
Variables	Normal Normal	Skewed STD	Normal	Skewed GED	GED	Skewed	GHYP
	Estim $p-$	Estim $p-$	Estim $p-$	Estim $p-$	Estim $p-$	Estim $p-$	Estim $p-$
ω	0.0000 (0.2900)	0.0000 (0.1422)	0.0000 (0.4622)	0.0000 (0.1542)	0.0000 (0.1660)	0.0000 (0.1180)	0.0000 (0.1153)
α_1	0.0664 (0.0000)	0.0693 (0.0000)	0.0637 (0.0000)	0.0656 (0.0000)	0.0659 (0.0000)	0.0678 (0.0000)	0.0665 (0.0000)
β_1	0.9513 (0.0000)	0.9487 (0.0000)	0.9533 (0.0000)	0.9511 (0.0000)	0.9512 (0.0000)	0.9500 (0.0000)	0.9501 (0.0000)
λ_1	-0.0597 (0.0000)	0.0589 (0.0000)	-0.00590 (0.0000)	-0.0574 (0.0000)	-0.0598 (0.0000)	-0.0585 (0.0000)	-0.0577 (0.0000)
Shape			12.3684 (0.0000)	13.78 (0.0000)	1.6728 (0.0000)	1.7014 (0.0000)	5.5450 (0.0985)
Skew		1.1818 (0.0000)		1.1729 (0.0000)		1.1780 (0.0000)	0.2495 (0.2233)
Ghlambda							0.5151 (0.9664)
$\alpha_1 + \beta_1$	1.0177	1.018	1.017	1.0167	1.0171	1.0178	1.0166
Goodness of fit							
AIC	-6.5204	-6.5340	-6.5319	-6.5421	-6.5279	-6.5398	-6.5405
BIC	-6.5106	-6.5217	-6.5196	-6.5274	-6.5156	-6.5251	-6.5234
Weighted Ljung-Box test on stdised res	Statistic (p-value)	Statistic (p-value)	Statistic (p-value)	Statistic (p-value)	Statistic (p-value)	Statistic (p-value)	Statistic (p-value)
Lag[1]	0.09092 (0.7630)	0.09717 (0.7553)	0.0860 (0.7693)	0.0898 (0.7644)	0.0923 (0.7613)	0.0926 (0.7609)	0.0934 (0.7599)
Lag[2*(p+q)+(p+q)-1][2]	0.32831 (0.7802)	0.35466 (0.7660)	0.3128 (0.7886)	0.3351 (0.7765)	0.3251 (0.7819)	0.3453 (0.7710)	0.3409 (0.7734)
Lag[4*(p+q)+(p+q)-1][5]	1.66808 (0.6986)	1.69792 (0.6913)	1.6489 (0.7033)	1.6734 (0.6973)	1.6641 (0.6996)	1.6871 (0.6939)	1.6801 (0.6956)
Weighted Ljung-Box test on stdised res sqd	Statistic (p-value)	Statistic (p-value)	Statistic (p-value)	Statistic (p-value)	Statistic (p-value)	Statistic (p-value)	Statistic (p-value)
Lag[1]	0.0079 (0.9293)	0.0073 (0.9320)	0.0424 (0.8368)	0.0028 (0.9576)	0.0141 (0.9055)	0.00069 (0.9791)	0.00023 (0.9878)
Lag[2*(p+q)+(p+q)-1][5]	8.6262 (0.0206)	7.6770 (0.0354)	9.4062 (0.0131)	8.5947 (0.0209)	8.8389 (0.0182)	8.0101 (0.0293)	8.3632 (0.0239)
ARCH LM Tests	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic
ARCH Lag[3]	0.08097 (0.7760)	0.0265 (0.8706)	0.1400 (0.7083)	0.0748 (0.7845)	0.0901 (0.7640)	0.0452 (0.8317)	0.0572 (0.8110)
ARCH Lag[5]	0.2159 (0.9617)	0.2448 (0.9546)	0.2284 (0.9587)	0.2238 (0.9598)	0.2116 (0.9627)	0.2330 (0.9575)	0.2234 (0.9599)
ARCH Lag[7]	0.5459 (0.9740)	0.6671 (0.9609)	0.5025 (0.9782)	0.5692 (0.9717)	0.5285 (0.9757)	0.6205 (0.9662)	0.5901 (0.9695)

4.5. Discussions

Any evidence of an accurate VaR model can be described only by hit sequences that satisfy both unconditional coverage and independence properties (Campbell, 2005).

[8], in their use of GARCH based VaR in the emerging Montenegrin economy stock exchange, findings showed all their proposed GARCH models were insignificant under the Kupiec's test. The backtesting outcome in this study show that the majority of the proposed GARCH models are significant at both 95% and 99% levels of significance.

Table 6. **Back testing results for the EUR/USD exchange rate**

	Model Evaluation Results						
Variables	Normal Normal	Skewed STD	Normal	Skewed GED	GED	Skewed GED	GHYP
GARCH(1,1)							
99%							
KUPIEC'S	0.0621	0.0931	0.9237	0.3385	0.7595	0.3385	0.4614
Christoffersen's	0.1381	0.1854	0.7926	0.5416	0.7747	0.5416	0.6419
95%							
KUPIEC'S	0.7988	0.6820	0.2750	0.4702	0.9472	0.6130	0.4152
Christoffersen	0.5025	0.7331	0.0572	0.1070	0.6949	0.6797	0.1097
eGARCH(1,1)							
95%							
KUPIEC'S	0.0931	0.1933	0.6033	0.1586	0.6033	0.1586	0.1586
Christoffersen's	0.1854	0.3010	0.3583	0.1047	0.3583	0.1047	0.1047
95%							
KUPIEC'S	0.5920	0.9018	0.3175	0.6582	0.8723	0.4264	0.5293
Christoffersen	0.5226	0.6363	0.3167	0.5215	0.4852	0.3254	0.5180
GJR-GARCH(1,1)							
95%							
KUPIEC'S	0.1933	0.3606	0.7595	0.3385	0.7595	0.3385	0.4613
Christoffersen's	0.3010	0.4214	0.7747	0.5146	0.7747	0.5416	0.6418
95%							
KUPIEC'S	0.8270	0.8270	0.3643	0.8723	0.7535	0.3223	0.4703
Christoffersen	0.5986	0.5986	0.3275	0.2894	0.3432	0.2414	0.3391

This is in contrast to [8]. The significant result is of great benefit to the financial risk managers and practitioners in the third world economy, like Zimbabwe as it helps them in ascertaining the value they are likely to lose when they hold a portfolio in a certain currency under the multi-currency regime i.e. holding a portfolio in the South African Rand for instance.
The high p-values from backtesting results are proof of the superiority of proposed models especially under generalized error distribution (GED) and skewed student's t-distributed errors.
Although the normal distribution is a widely used model for errors, this research suggests that the generalized error distribution and skewed student's t-distribution help improve the modeling of the errors in the estimation of the volatility of currencies understudy. Risk practitioners in the third world countries can move away from the traditional normal error distribution and enhance their understanding of the risk to which their portfolios are exposed.

5. Conclusion and area of further study

5.1. Conclusion

In this study, the performance of selected GARCH-based VaR methodologies was explored in comparing risk inthree major currencies (South Africa's Rand (ZAR), EURO (EUR), and British pound (GBP)) used in Zimbabwe under the multi-currency regime. Three univariate GARCH based models were explored and implemented, these are GARCH (1,1), EGARCH(1,1), and GJR-GARCH(1,1), under seven error distributions were used in the estimation of the VaR. All GARCH models gave reliable results, which meant that the capacity of the models

Table 7. **Back testing results for the GBP/USD exchange rate**

	Model Evaluation Results						
Variables	Normal Normal	Skewed STD	Normal	Skewed GED	GED	Skewed GED	GHYP
GARCH(1,1)							
99%							
KUPIEC'S	0.0158	0.1359	0.6044	0.9111	0.7519	0.9111	0.9111
Christoffersen's	0.0311	0.2172	0.6533	0.7754	0.7266	0.5088	0.7754
95%							
KUPIEC'S	0.6582	0.9472	0.0687	0.1011	0.5920	0.7273	0.0837
Christoffersen	0.2738	0.3790	0.1450	0.2043	0.8508	0.8125	0.1702
eGARCH(1,1)							
99%							
KUPIEC'S	0.0256	0.0931	0.6044	0.7595	0.9237	0.6033	0.4614
Christoffersen's	0.0488	0.1568	0.5034	0.4229	0.4743	0.3583	0.2877
95%							
KUPIEC'S	0.7273	0.3722	0.0367	0.1215	0.8723	0.9018	0.1215
Christoffersen	0.5666	0.6006	0.0237	0.0938	0.6430	0.7187	0.0938
GJR-GARCH(1,1)							
99%							
KUPIEC'S	0.0096	0.0931	0.7519	0.9111	0.9237	0.6033	0.9237
Christoffersen's	0.0192	0.1568	0.7266	0.7754	0.7926	0.7227	0.7926
95%							
KUPIEC'S	0.5293	0.9472	0.0688	0.0837	0.5920	0.6033	0.1012
Christoffersen	0.4340	0.3790	0.1405	0.1702	0.7123	0.6430	0.2043

depends on the particular asset under consideration.

Backtesting techniques recommend the GARCH(1,1) with generalized error distribution is the optimal model for the EUR/USD rate, Whilst for GBP/USD and ZAR/USD, GJR -GARCH(1,1) with GED and GARCH (1,1) skewed STD are optimal models respectively. The GARCH(1,1) with generalized error distribution is recommended as the optimal model.

Hence, financial risk managers can use the findings to compute the capital required to cushion themselves in the event that the loss estimated by VaR occurs. The results further aids risk practitioners' decision on the preferred currency as a means of storage/preservation of value since Zimbabwe is under a multi-currency regime.

Volatility persistence coefficients suggests that it would be safe for Zimbabwe's risk practitioners to keep savings in GBP than in any other currencies consideredunder thisstudy.

5.2. Areas of Further Study

This study contributes to an investigation into the improvements in the computation of VaR by means of various univariate GARCH models. Extreme Value Theory(EVT)gives models that are able to capture extreme losses, hence extreme risk. EVT models will be considered in future research.

Table 8. **Back testing results for the ZAR/USD exchange rate**

	Model Evaluation Results						
Variables	Normal Normal	sNormal	STD	SSTD GED	GED	SGED	GHYP
GARCH(1,1)							
99%							
KUPIEC'S	0.0001	0.0158	0.0056	0.9111	0.0056	0.4732	0.9237
Christoffersen's	0.0003	0.0468	0.0144	0.9472	0.0195	0.5472	0.9472
95%							
KUPIEC'S	0.0561	0.9773	0.0144	0.9472	0.0561	0.4732	0.9237
Christoffersen	0.1282	0.4372	0.0280	0.4632	0.1282	0.4179	0.4632
eGARCH(1,1)							
99%							
KUPIEC'S	0.0010	0.0404	0.0158	0.7519	0.0158	0.6044	0.7519
Christoffersen's	0.0042	0.0994	0.0184	0.5293	0.0468	0.8723	0.5293
95%							
KUPIEC'S	0.0367	0.7273	0.0184	0.5293	0.0366	0.3606	0.6044
Christoffersen	0.0505	0.3190	0.0329	0.3395	0.0505	0.4214	0.5034
GJR-GARCH(1,1)							
99%							
KUPIEC'S	0.0001	0.0256	0.0056	0.4732	0.0056	0.3606	0.6044
Christoffersen's	0.0007	0.0693	0.0087	0.5293	0.0195	0.9773	0.5293
95%							
KUPIEC'S	0.0233	0.5920	0.0087	0.5293	0.0367	0.9773	0.5293
Christoffersen	0.0537	0.7137	0.0136	0.6946	0.0730	0.6687	0.6946

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