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Modelling Change Point in GARCH Models

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Abstract This research paper use PELT algorithm and GARCH models to conduct volatility change point analysis and to model and forecast change point in volatility of USD/KES data. This study employed simulated data and data from Central Bank of Kenya for the period between January 2005 to December 2018. The estimates and actual values of change points in volatility did not differ after analysis. The USD/KES data exhibited volatility clustering in some time periods. The volatility adjusted GARCH models outperformed plain models. The simulated estimates of GARCH models were almost converging to the parameters from USD/KES data using the same models. The GARCH models that incorporate change points registered better forecasting performance compared to the plain models. The PGARCH, TGARCH and GJRGARCH models had the same forecasting performance measures in absence and presence of change points. The study recognized TGARCH (1,1) as the best model for modelling and forecasting. Banks can use univariate GARCH models in conjunction with PELT algorithm to track loan defaulters. Hospitals can use the same technique to determine the most recurring diseases. Companies can apply the same to determine abnormal profits and losses. The technique can be applied in other sectors like in meteorology.

Keywords: *change point, PGARCH, TGARCH, GJRGARCH, volatility*

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1. Introduction

1.1. Background of the Study

The Nairobi Securities exchange is one of the leading African exchange situated in Kenya. It is one of the fastest growing economies in Africa. The exchange offers the best platform for local and international traders to do trading and accumulate wealth. Over the years, this sector has received significant growth thereby sparking growth in the Kenyan economy. There are a number of currencies being traded in the Nairobi securities exchange. Among them is the United States dollars in relation to Kenya shillings.

The USD/KES has been highly volatile leading to the Kenyan currency always lose purchasing power compared to the United States Dollar. The persistent in volatility of USD against KES has brought volatility clustering. This has majorly exposed the economy and all stakeholders who have invested or have plans of investing to the risks and eventual losses they may incur as a result of volatility.

When a shilling weakens, this make it lose its purchasing power and eventually, the economy cripples. Many players in the economy e.g. investors are always hard hit by the loss of purchasing power of the Kenyan shilling. Therefore, coming up with the best model and algorithm in modelling and detecting change in volatility and also in forecasting future change in volatility can stabilize this exchange market by making sure that investors don’t lose their investments and making sure that the economy thrives. In addition, this would help government agencies in providing favorable policies that would help curb against any form of volatility now and in the future.

Volatility refers to the conditional variance of the underlying asset return and is measured as the sample standard deviation. Volatility clustering refers to a situation where large returns are followed by large returns and vice versa which extends in regimes of abnormally high or low volatility.

Studies conducted in various parts of the world present mixed findings regarding use of GARCH models especially when discussing the issue of volatility in a time series data. But the question that seems to be on the minds of many other scholars is the fact that how effective are the GARCH models in modelling change in volatility. Generally, there has been a consistent opinion that the models remain effective when dealing with such volatile data. Johansson [1] who recently conducted a study on Stockholm stock exchange (OMXS30) and the Milano stock exchange index (MIB30) laid an emphasis on the effectiveness of GJR GARCH model especially in order to predict changes in financial assets as stocks.

Change point analysis refers to a situation where there are change points in a dataset. The main purpose of identifying change point is so as to know the number of changes and their locations so that we can correct such changes. Change points are treated as abnormal behaviors in the specific area of study. Detecting multiple change points is crucial in many areas. E.g. in finance, meteorology, medical field and among other areas.

Change points increase with increase in data points. This has been a challenge in statistics, to know the actual change points and their locations. Bearing in mind that most companies are handling big data, they want to know the abnormalities of these datasets by determining the change points. The challenge is how to handle such data and methods of change points detection. Many methods have been proposed like binary segmentation algorithm, segment neighborhood and the pruned exact linear time. PELT is an accurate algorithm.

Verma and Ghosh [2] whose study was conducted in India pointed out the fact that change point analysis is one of the most powerful tools that can be used for detection of change point in a given time series data.

A study conducted in India by Singh and Tripathi [3] highlighted the importance of use of both TGARCH and PGARCH models in modelling volatile stock data and exchange data.

A keen look at the studies in the literature reveal that little has been done in terms of modelling change point in volatility of data from the Central Bank of Kenya. The study seeks to fill this gap by coming up with the best model to fit and forecast volatility change in the Kenya securities market, more so USD/KES exchange rates. The PELT algorithm will be used to detect change points in volatility as it is more accurate

2. Review of Previous Studies

In a study by Włodarczyk and Kadłubek [4] focusing on risk management of carbon emissions, was able to determine that GARCH model is one of the most important models in forecasting volatility of such data

A study conducted by Dutta [5] established that the use of power GARCH models played an important role especially in order to model and forecast the US ethanol price precisely to minimize the market risk. The current study however focuses on the context of Kenya by using data from the Central Bank of Kenya to analyze the change points of the volatility with the purpose of coming up with a model to forecast volatility.

In a study focusing on studying the capital markets dynamics in South East Europe, Stoykova and Paskaleva [6] highlighted the importance of making use of PGARCH models in forecasting volatility in time series data relating to the capital markets.

Sarwar [7], who recently conducted a study in America argued that use of TGARCH models can be effective especially in the efforts to understand the process of transmission of risks between US and emerging equity markets. Sarwar and Khan [8] emphasized on the utilization of TGARCH model especially in order to understand the interrelations of market fears and emerging markets returns.

Jiang and Hua [9] recently conducted a study in China and utilized the threshold GARCH with generalized error distribution (TGARCH-M with GED) in order to analyze models related to what is referred to as option pricing which plays an important role in risk management and investment strategies.

Mozumder et al. [10] emphasize on the importance of using Glosten, Jagannathan and Runkle generalized autoregressive conditional heteroscedasticity (GJR-GARCH) in carrying out volatility dynamics. A recent study conducted by Chun, Cho and Ryu [11] pointed out that GJR GARCH is one of the best performing volatility forecasting models in the GARCH-family volatilities.

It has been demonstrated in a recent study on American oil industry that utilization of GJR GARCH plays an important role in forecasting volatility of time series data Bedoui, Braiek, Guesmi & Chevallier [12]. After carrying out a study in order to make a comparison between volatility of dependency between US dollar and Euro, Jamel and Mansour [13] were able to incorporate GJR GARCH as one of the most important models in studying volatility.

In Europe, a study conducted by [2] on Stockholm stock exchange (OMXS30) and the Milano stock exchange index (MIB30) for the period 31st of October 2003 to 30th of December 2008 emphasize the importance of use of GJR GARCH model especially in order to predict changes in financial assets like stocks.

Allen, McAleer, Powell and Singh [14] define change point analysis as the process of assessing distributional changes within the time for that observations. In contrast, Pereira and Ramos [15] clarifies the fact that conducting change point analysis mostly focuses on determining the changes in both mean and variance in a given time series data sets

Ref. [2] in a study conducted in India posit that change point analysis can be a powerful tool that can be used for detection of a change that has occurred in a time series data sets over a long period of time.

The current study uses the context of Kenya by utilizing the data from the Central Bank of Kenya between the year 2005 to 2018 with a purpose of first and foremost conducting change point analysis for the volatility and also at the same time making use of TGARCH and PGARCH, and GJR GARCH models for the purposes of coming up with the model that can be used for forecasting volatility in time series data especially one that relates to the financial sector such as the Central Bank of Kenya.

3. Methodology

3.1. Multiple Change Point Detection

In this study multiple change detection was used. The general equation that is minimized to get the change points will take the form:

$$\sum_{i=1}^{m+1}\left[C(y_{\tau_{i-1}+1},\ldots,y_{\tau_i}\right]+\beta f(m) \qquad (1)$$

Where C is a cost function for a segment and $\beta f(m)$ is a penalty to guard against over fitting (a multiple change point version of the threshold c). In the literature, the cost function that is mostly used is twice the negative likelihood function. Mostly on the ground, the penalty that is commonly used is the one that is linear in terms of change points. I.e. $\beta f(m) = \beta\, m$ .Examples of some penalties are AIC, ($B = 2p$) and BIC ,$B = plogn$ where p is and additional parameter achieved after having an additional change point. Such linear functions tailored for PELT algorithm.

3.2. The Pruned Exact Linear Time (PELT) Method

The method, a pruning step within dynamic programming technique to obtain the optimal segmentation for $(m + 1)$ change points was used. The method proposed to minimize

$$\sum_{i=1}^{m+1}[C\left(y\left(y_{\tau_{i-1}+1},\ldots,y_{\tau_i}\right)+\beta\right] \tag{2}$$

C is the cost function and B is the penalty to guard against overfitting.

The PELT method combines optimal partitioning and pruning to get accurate and proper linear computational cost. The optimal segmentation is $F(P)$ where

$$F(p)=\min_{\tau}\left\{\sum_{i=1}^{m+1}\left[C\left(y_{\tau_{i-1}+1},\ldots,y_{\tau_i}\right)+\beta\right]\right\} \tag{3}$$

when conditioned to the last change point τ_m and then solving data segmentation to that change point results to

$$F(p)=\min_{\tau_m}\{\min_{\tau/\tau_m}\{\sum_{i=1}^{m+1}\begin{bmatrix}\left[C\left(y_{\tau_{i-1}+1},\ldots,y_{\tau_i}\right)+\beta\right]\\ +C\left(y_{\tau_m+1},\ldots,y_{\tau_p}\right)\end{bmatrix}\} \tag{4}$$

This can be recursively repeated from the second change point to the last. The inner minimization is equal to $F(\tau_m)$ and therefore equation (4) Can be written as

$$F(p)=\min_{\tau_m}\left\{F(\tau_m)+C\left(y_{\tau_m+1},\ldots,y_p\right)\right\} \tag{5}$$

F (1) is first calculated and then F (2), F (3) … are calculated recursively. For every step, the optimal segmentation up to τ_{m+1} is stored. When F(n) is reached, the optimal segmentation of the whole data would have been identified. Also, the number of locations in the dataset would have been known.

3.3. Asymmetrical GARCH Modelling

After the volatility regimes have been clearly identified by the use of PELT, the next step will be to model the structural breaks or change points using PGARCH, TGARCH and GJRGARCH models. The PGARCH proposed by Ding et al. [16] generalizes the transformation of error terms in the models. The variance equation of the PGARH model is given as

$$\sigma_t^2=\omega+\sum_{i=1}^{p}(\propto_i|b_{t-i}|-\gamma_i b_{t-i})^{\delta}+\sum_{j=1}^{q}\beta_J\sigma_{t-j}^{\delta} \tag{6}$$

Where $\omega > 0$, $\delta > 0$, $\propto_i \geq 0$, $\propto_i \geq 0$, $-1 < \gamma_i < 1$, $i = 1, \ldots, p$, $\beta_j \geq 0, j = 1, \ldots, q. \propto_i$ and β_j are the standard ARCH and GARCH parameters. γ_i's are the leverage parameters and δ is the parameter for the power term. The model sets $\gamma_i = 0$ for all i. When $\delta = 2$, equation becomes a classic GARCH model that allows for leverage effect. The standard deviation will be estimated when $\delta = 1$.

The TGARCH model was proposed by Glosten, Jagannathan and Runkle [17] and Zakoian [18] with an aim of handling asymmetrical effect.

A variance equation of TGARCH model (p, q) is written as:

$$\sigma_t^2=\omega+\sum_{i=1}^{p}(\propto_i+\gamma_i K_{t-i})b_{t-1}^2+\sum_{j=1}^{q}\beta_J\sigma_{t-j}^2 \tag{7}$$

Where K_{t-i} is a dummy variable (indicator) for negative b_{t-1}^2, I.e. $b_{t-1}^2 = \begin{cases}1\ if\ b_{t-1}^2 < 0\\ 0\ if\ b_{t-1}^2 \geq 0\end{cases}$.

And $\propto_i, \gamma_i$, and β_J are non-negative parameters.

The model uses zero so as its threshold to separate impacts of past shocks.

The GJRGARCH model was proposed by [17]

The variance equation of GJR-GARCH (p, q) is given by:

$$\sigma_t^2=\omega+\sum_{i=1}^{p}\propto_i b_{t-1}^2+\sum_{j=1}^{q}\beta_J\sigma_{t-j}^2+\gamma_i I_{t-i}b_{t-1}^2 \tag{8}$$

Where $\alpha, \beta\ and\ \gamma$ are constant parameters, and I is an indicator function (dummy variable) that takes the value zero when b_{t-i} is positive (negative). If γ is positive, negative errors are leveraged (negative innovations or bad news have greater impact than the positive ones). The model parameters are assumed to be positive and that $\alpha + \beta + {}^{\gamma}/_{2} < 1$.

In all the models, the best volatility GARCH model would be selected on the basis of AIC and BIC.

4. Results and Discussions

4.1. Data

Simulated PGARCH, TGARCH and GJR data was used. Also daily data from Central Bank of Kenya (CBK) for a time period between January 2005 to December 2018 was used in the analysis. R package was used for analysis.

Figure 1 depict a plot of PGARCH, TGARCH and GJRGARCH simulated models with two change points set at points 500 and 1001. From the figure, it can be clearly seen that there are two change points and two change points locations. It can also be seen that there are three data change regimes.

Figure 2 confirm two change points for each of the models. I.e. at points 500 and 1001. These change points are marked by vertical red lines. These points calculated by PELT algorithm are the exact change points. The points are the same as the change points set during simulation.

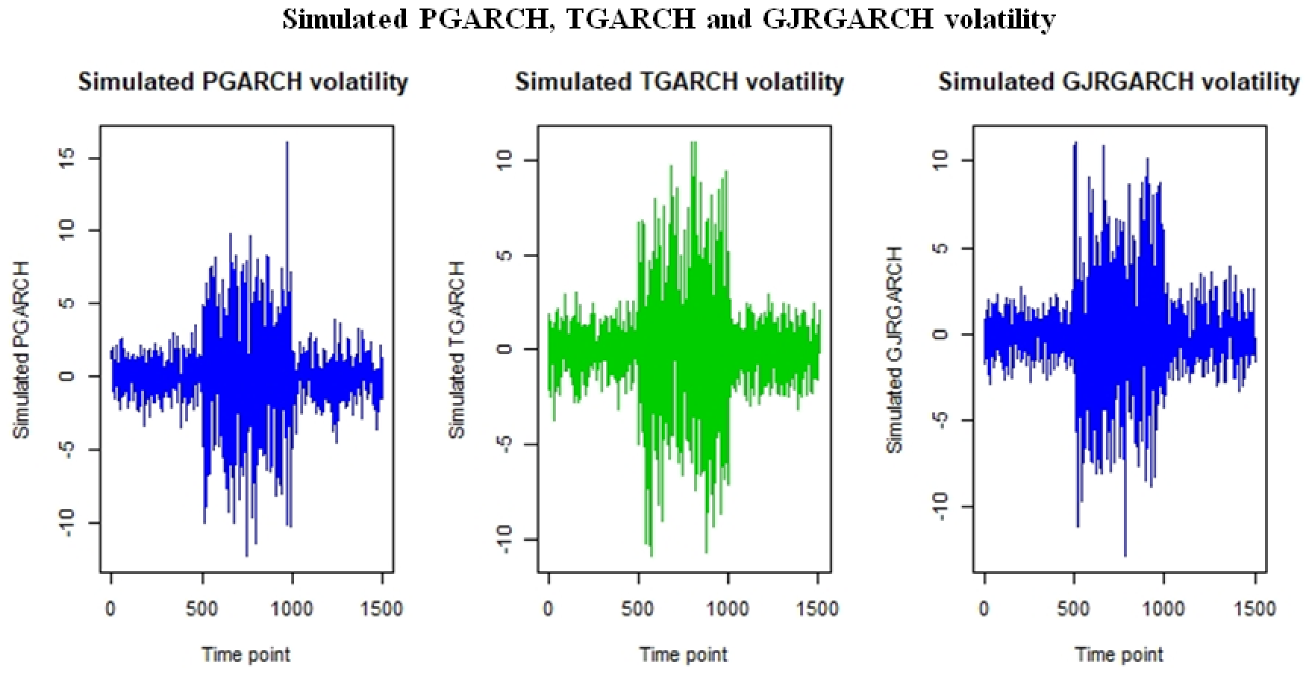

Figure 1. A plot of PGARCH, TGARCH and JGRGARCH volatility before PELT algorithm

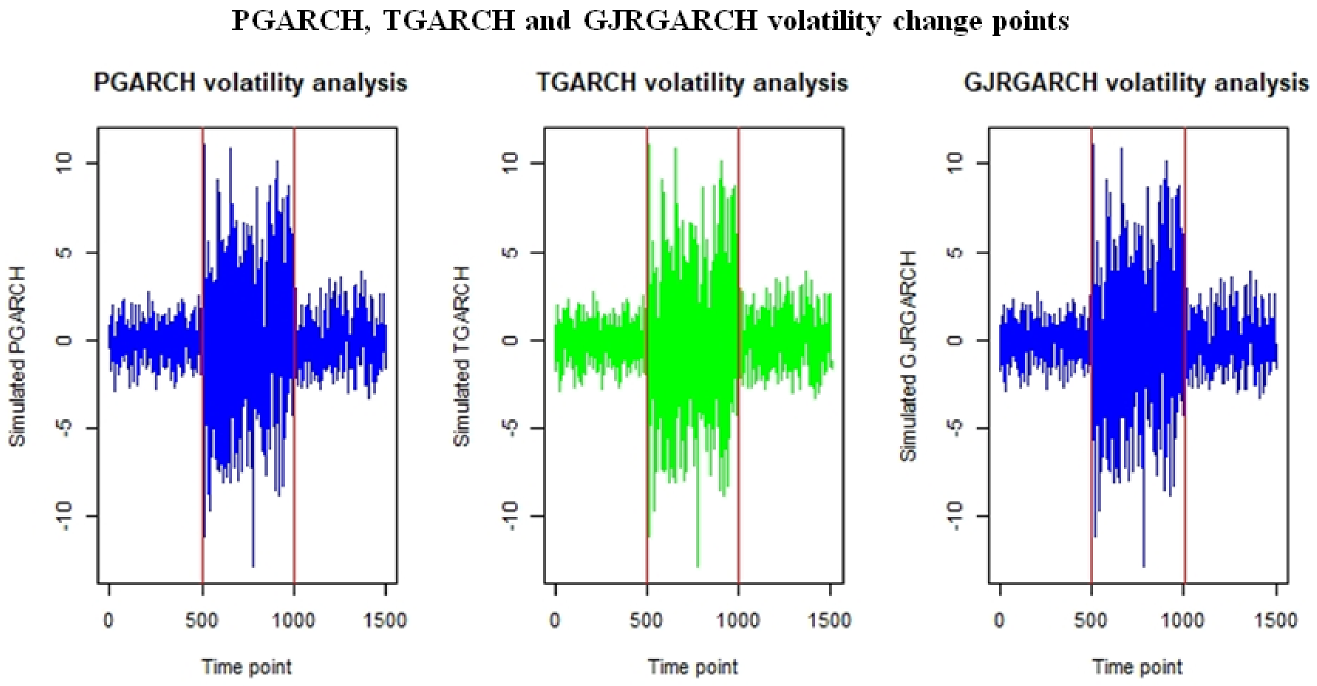

Figure 2. A plot of PGARCH, TGARCH and JGRGARCH volatility structural breaks after PELT algorithm

4.2. Change Points in GARCH Models

After confirming that the estimates from simulations were the same as actual values from PELT algorithm, different models were fitted to the three data regimes created by the two structural breaks with an aim of getting average parameters of each model. The aim was to compare the parameters of each data regime across the models with the parameters of the models when using whole data for each model to see whether there was change in parameters of models with structural changes and those without. The parameters of the whole data were different from parameters of each data regime of the corresponding model. This shows change in parameters that reflect change in volatility data.

Table 1 give parameters of PGARCH, TGARCH and GJRGARCH at change points 500 and 1001. The table also shows average parameters of the models after incorporating change points.

4.3. True and Estimated Parameters of GARCH Models

Table 2. indicate that the true and estimated parameters of PGARCH, TGARCH and GJRGARCH at change

points 500 and 1001 are close to each other. Therefore, the estimated parameters are better estimates of true parameters.

After getting average parameters, goodness of fit measures were also calculated with an aim of comparing performance of the models with and without inclusion of change points.

Table 3 give averages of model fit measures of PGARCH, TGARCH and GJRGARCH models with change points at 500 and 1001.

Table 1. parameters of GARCH models at change points 500 and 1001

	Omega	alpha1	beta1	etal1	gamma1	lambda	shape
$PGARCH_1(1,1)$	0.456	0.001	0.507	1.000		4.000	100.000
$PGARCH_2(1,1)$	2.618	0.022	0.529	-0.862		2.714	100.000
$PGARCH_3(1,1)$	0.319	0.067	0.000	0.055		4.000	96.883
$Average\ PGARCH(1,1)$	**1.131**	**0.003**	**0.345**	**0.064**		**3.571**	**98.961**
$TGARCH_1(1,1)$	0.114	0.064	0.844	-0.320			30.603
$TGARCH_2(1,1)$	0.211	0.010	0.940	1.000			60.364
$TGARCH_3(1,1)$	0.930	0.198	0.000	-0.109			100.000
$Average\ TGARCH(1,1)$	**0.418**	**0.091**	**0.595**	**0.190**			**63.653**
$GJRGARCH_1(1,1)$	0.001	0.000	1.000		-0.021		
$GJRGARCH_2(1,1)$	0.105	0.000	1.000		-0.013		
$GJRGARCH_3(1,1)$	0.004	0.000	1.000		-0.346		
$Average\ GJR(1,1)$	**0.037**	**0.000**	**1.000**		**-0.346**		

Table 2. True and estimated parameters of GARCH models at change points 500 and 1001

	Omega		alpha1		beta		gamma1	
	Estimate	true	estimate	true	estimate	true	estimate	true
$PGARCH_1(1,1)$	0.456	0.54	0.001	0.54	0.507	0.93		
$PGARCH_2(1,1)$	2.618	0.13	0.022	0.13	0.529	0.47		
$PGARCH_3(1,1)$	0.319	0.95	0.067	0.95	0.000	0.43		
$Average\ PGARCH(1,1)$	**1.131**	**0.54**	**0.003**	**0.54**	**0.345**	**0.61**		
$TGARCH_1(1,1)$	0.114	0.23	0.064	0.01	0.844	0.43		
$TGARCH_2(1,1)$	0.211	0.13	0.010	0.68	0.940	0.37		
$TGARCH_3(1,1)$	0.930	1.45	0.198	0.05	0.000	0.23		
$Average\ TGARCH(1,1)$	**0.418**	**0.60**	**0.091**	**0.247**	**0.595**	**0.34**		
$GJRGARCH_1(1,1)$	0.001	0.004	0.000	0.040	1.000	0.930	-0.021	0.040
$GJRGARCH_2(1,1)$	0.105	0.127	0.000	0.050	1.000	0.87	-0.013	0.100
$GJRGARCH_3(1,1)$	0.004	0.056	0.000	0.060	0.930	1.000	0.930	-0.860
$Average\ GJR(1,1)$	**0.037**	**0.066**	**0.000**	**0.050**	**1.000**	**0.910**	**-0.346**	**-0.720**

Table 3. Average AICs and BICs of GARCH models

	AIC	BIC
$PGARCH_1(1,1)$	2.8570	2.9160
$PGARCH_2(1,1)$	5.8349	5.8938
$PGARCH_3(1,1)$	3.0813	3.1401
$Average\ PGARCH(1,1)$	**3.9244**	**3.9833**
$TGARCH_1(1,1)$	2.9956	3.0462
$TGARCH_2(1,1)$	5.6311	5.6816
$TGARCH_3(1,1)$	3.0466	3.0970
$Average\ TGARCH(1,1)$	**3.8911**	**3.9416**
$GJRGARCH_1(1,1)$	2.7979	2.8401
$GJRGARCH_2(1,1)$	5.7128	5.7448
$GJRGARCH_3(1,1)$	3.2929	3.3349
$Average\ GJR(1,1)$	**3.9345**	**3.9733**

Table 4. Model fit measures of AICs and BICs with average change points and without change points.

	AIC	BIC
With average change points		
PGARCH(1,1)	3.9244	3.9833
TGARCH(1,1)	3.8911	3.9416
GJRGARCH(1,1)	3.9345	3.9733
Without change points		
PGARCH(1,1)	3.9594	3.9840
TGARCH(1,1)	3.9298	3.9511
GJRGARCH(1,1)	4.0156	4.0333

4.4. Model Estimation Comparison

Table 4 give AICs and BICs of asymmetrical GARCH models in presence and absence of change points. The models approximated with structural breaks are better compared to plain models. This is marked by the models incorporating change points registering the lowest AICs and BICs. The TGARCH model is the best fitting model with and without change points. This is because it has the lowest AIC and BIC.

4.5. Real Data Analysis

The Forex data from the Central Bank of Kenya from January 2005 to December 2018 was also modelled using GARCH models with an aim of analyzing change in volatility of USD/KES data.

The volatility data was plotted as shown in Figure 3. Through visualization, volatility clustering can be witnessed, a clear indication of presence of change in volatility.

After application of PELT algorithm, a total of 4 change points for the volatility were realized, which means that volatility persistently changed at 4 points. This implies that the USD/KES is highly volatile. The change is shown in Figure 4.

Figure 4 indicate that volatility of USD/KES has changed at 4-time points. The abrupt change indicates turbulent times between December 2006 and February 2010, and around January to June 2012. This was as a result of pre and post-election crisis that erupted because of 2007 and due to Eurobond bought by government in 2012.

4.5.1. Average Parameters of USD/KES Data

The volatility change points of USD/KES were then fitted in the models with an aim of getting average parameters that would be used for comparison purposes with the simulation results.

4.5.2. Average Estimates from Simulated GARCH and USD/KES Data

Table 6 shows GARCH models average simulated values and actual values from forex data. There is no much difference between simulated values and estimates from forex data except for shape parameter. This indicates that simulations can be used to model practical phenomena and register better results.

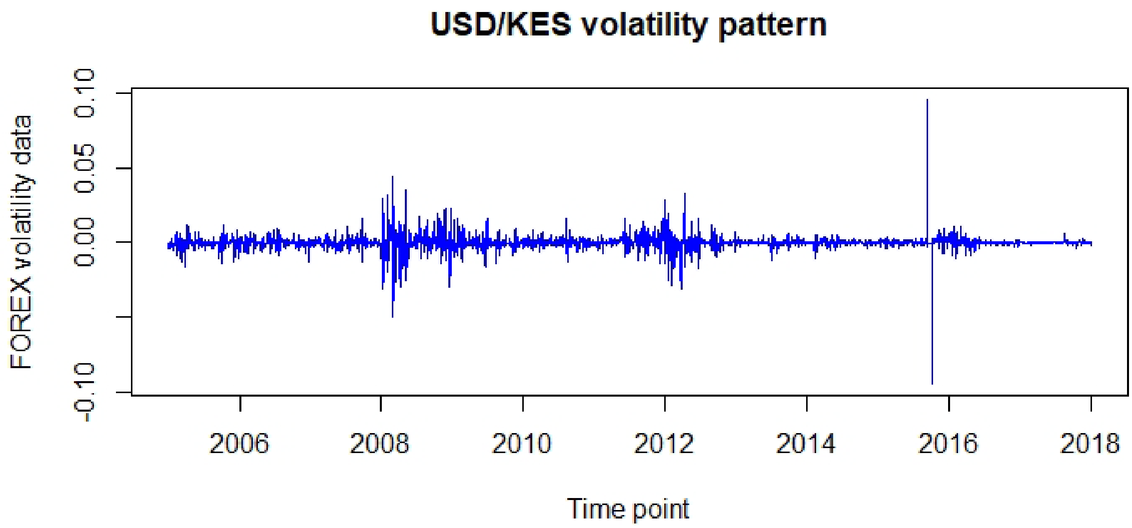

Figure 3. Plot of volatility data

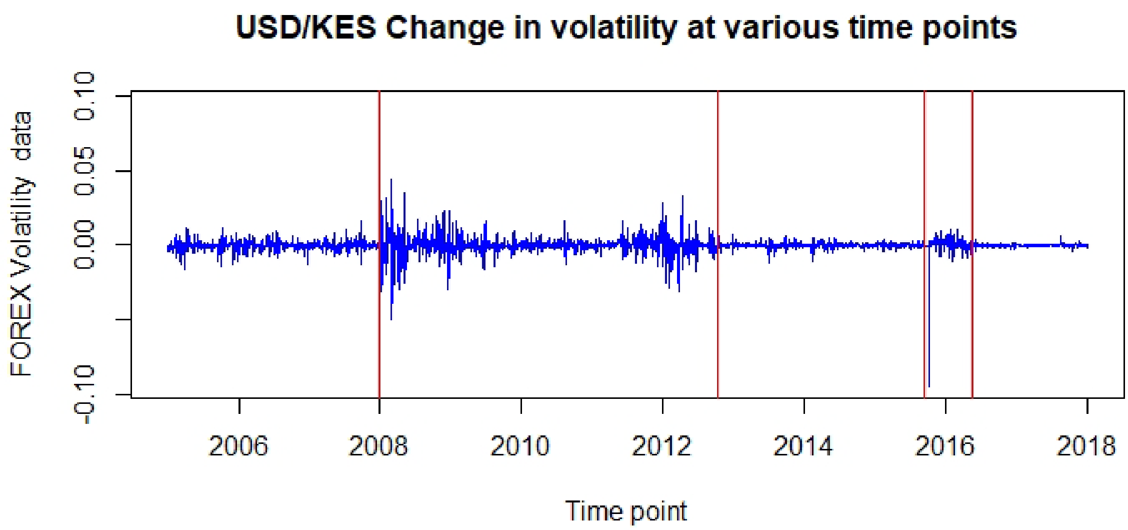

Figure 4. A plot of structural breaks in the volatility of USD/KES data

Table 5. Average parameters of GARCH models at points 716,1863,2565,2729

	Omega	alpha1	beta1	etal1	gamma1	lambda	shape
$PGARCH_1(1,1)$	0.001	0.670	0.675	-0.180		0.988	2.100
$PGARCH_2(1,1)$	0.000	0.386	0.748	-0.129		1.012	2.776
$PGARCH_3(1,1)$	0.000	0.120	0.764	0.088		2.256	3.602
$PGARCH_4(1,1)$	0.001	0.310	0.833	-0.179		0.385	2.100
$PGARCH_5(1,1)$	0.000	0.038	0.946	0.366		2.073	2.746
$Average\ PGARCH(1,1)$	**0.004**	**0.305**	**0.793**	**-0.007**		**1.343**	**2.665**
$TGARCH_1(1,1)$	0.001	0.678	0.677	-0.178			2.100
$TGARCH_2(1,1)$	0.002	0.384	0.748	-0.130			2.775
$TGARCH_3(1,1)$	0.002	0.376	0.763	0.067			3.171
$TGARCH_4(1,1)$	0.000	0.280	0.916	-0.732			2.100
$TGARCH_5(1,1)$	0.003	0.409	0.481	0.220			2.598
$Average\ TGARCH(1,1)$	**0.004**	**0.426**	**0.717**	**-0.151**			**2.549**
$GJRGARCH_1(1,1)$	0.000	0.090	0.865	-0.113			
$GJRGARCH_2(1,1)$	0.000	0.224	0.802		-0.054		
$GJRGARCH_3(1,1)$	0.000	0.227	0.562		0.300		
$GJRGARCH_4(1,1)$	0.000	0.001	1.000		-0.008		
$GJRGARCH_5(1,1)$	0.000	0.424	0.460		-0.056		
$Average\ GJR(1,1)$	**0.000**	**0.203**	**0.738**		**0.034**		

Table 6: Average estimates of simulated PGARCH, TGARCH and GJR GARCH and average estimates from USD/KES data

	Omega	alpha1	beta1	etal1	gamma1	lambda	shape
Average simulated PGARCH values	1.131	0.003	0.345			3.571	98.961
Average PGARCH estimates from USD/KES data	0.004	0.305	0.793			1.343	2.665
Average simulated TGARCH values	-0.023	0.114	0.064	-0.320			30.603
Average TGARCH values from USD/KES data	0.004	0.426	0.717	-0.151			2.549
Average simulated GJRGARCH Estimates	0.001	0.000	1.000		-0.021		
Average GJRGARCH parameters from USD/KED data	0.000	0.203	0.738		0.034		

4.6. Predictive Ability of GARCH Models.

Table 7 shows forecasting performance of the PGARCH, GJRGARCH and PGARCH models with and without change points. It can clearly be seen from the table that all the models do forecasting well in presence of change points. This is because all the models have the least MSEs and MAEs compared to models without change points. The PGARCH, TGARCH and GJR GARCH models have the same forecasting performance with and without change points.

Table 7. Forecasting measures with and without change points

	MSE	MAE
With average change points		
PGARCH(1,1)	0.10909	0.191294
TGARCH(1,1)	0.10909	0.191294
GJRGARCH(1,1)	0.10909	0.191294
Without change points		
PGARCH(1,1)	0.2703	0.2435
TGARCH(1,1)	0.2703	0.2435
GJRGARCH(1,1)	0.2703	0.2435

5. Conclusion

The USD/KES rates has been marked by high and low volatility fluctuations. Despite plenty of local studies exploring various aspects of volatility in Nairobi stock exchange, little remains to be shown in literature as to how to carry out change point analysis and forecasting especially by utilization of data from the Central Bank of Kenya between the year 2005 and 2018 and using PELT. This research was thus directed in modelling volatility change in the USD/KES data using PELT algorithm. The simulated data was also compared from USD\KES data by use of parameters. The forecasting performance of PGARCH, TGARCH and GJR GARCH models were compared in presence and absence of change points. It was concluded that the volatility adjusted PGARCH, TGARCH and GJR GARCH models outperformed plain PGARCH, TGARCH and GJR GARCH models that didn’t incorporate structural changes. The estimates from simulated models were almost converging with the parameters from the USD\KES data. This is an indication that simulations can be used in different sectors of the economy to replicate true phenomena. Banks, insurance companies, investors among other stake holders can comfortably apply univariate GARCH models in conjunction with PELT algorithm in order to model and forecast uncertainties in their businesses long term plans. This would by large avert any huge losses that would have otherwise crippled their businesses. Researchers can conduct a similar study in different sectors other than in finance and especially in insurance and meteorological department in order to establish performance of these models. It is also recommended that it is important for industry stakeholders especially in the financial sector to carry out regular change point analysis especially in order to be able to discover some of the important trends with regards to changes in volatility of the time series data in order to take any necessary corrective measures.

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