Journal of Statistical and Econometric Methods, Vol 12, No 4, 2023, 39-53
ISSN: 2241-0384 (print), 2241-0376 (online)
https://doi.org/10.47260/jsem/1242
Scientific Press International Limited

Modeling and Forecasting Exchange Rate Volatility in West Africa using GARCH models

Didier Dukundane[1]

Abstract

This study empirically investigates the nature of exchange rate volatility in the context of West Africa. The study uses daily data on the exchange rates of the West African CFA franc (XOF) in terms of US Dollar. The empirical analysis has been carried out for the period from 13-11-2009 to 18-09-2023, for a total of 5058 observations. We excluded the last 25% of observations in order to evaluate the forecasting accuracy. The exchange rate volatility of the West African CFA franc against the US Dollar is estimated using GARCH models based on normal and student's t-distribution of innovations. Results show that the ARMA(3,1)-GARCH(1,2) model with student-t distribution is well adequate model to capture the mean and the volatility process of USD-CFA exchange rate log returns.

Keywords: Exchange rates, normal and student-t distribution, ARMA-GARCH.

[1] African Institute for Mathematical Science, AIMS-Ghana.

Article Info: Received: September 30, 2023. Revised: October 23, 2023.
Published online: October 30, 2023.

1. Introduction

Exchange rate fluctuation is seen as a general phenomenon around the globe which might have adverse effect on trade (De Grauwe, 1988). Economists are still very interested in the operations involved in the exchange rate especially in developing countries (Rose, 2000). Trade rate instability is said to likely have a negative impact on international trade as bilateral trade is threatened by the risks involved (Didier D, 2014). The economic relationship supporting the negative link is the unwillingness of firms to take on risky activity, namely trade (Reinhart and Rogoff, 2004). In this work, we broadly describe the exchange rate of CFA francs against U.S Dollars and investigate whether GARCH models are accurate in the evaluation of exchange rate volatility on the basis of daily exchange rates, using mid-market rates data from Friday 13-11-2009 to Monday 18-09-2023. Those data are collected from the Central Bank of West African States through their website. The CFA franc stands for African Financial Community; the coin used by WAEMU (West African Economic and Monetary Union: Togo, Mali, Guinea-Bissau, Senegal, Burkina Faso, Niger, Ivory Coast and Benin). This currency is pegged to the Euro, with a settled trade rate (one Euro likens to 655.957 CFA) and as an inheritance of the ”Africa French colony’s francs” is convertible only thanks to the French treasury guarantee. An international exchange rate, also known as the foreign exchange (FX) rate, is the rate at which one currency can be exchanged for another currency (Cooper, 2014). Remote trade rates, in reality, are one of the foremost important determinants of a country’s relative level of economic health (Frieden, 2016). It includes a solid affect on the financial improvements, remote coordinate speculation streams, worldwide exchange and capital versatility. Therefore, measuring volatility, which is the dispersion of exchange rate returns, has useful and practical applications for risk management, and policy evaluation, academics, policymakers, regulators, and market practitioners. More practically, understanding and estimating exchange rate volatility is important for exchange rate pricing, portfolio allocation, and risk management. Traders and regulators must consider not only the expected return from their trading activity but also risk exposure during volatile periods since traders’ performance is highly affected by the accuracy of volatility forecasts (Flannery and James, 1984). In 1982, Robert Engle developed the Autoregressive Conditional Heteroskedasticity (ARCH) model to model the time-varying volatility often observed in economic time series data (Engle, 1982). For this contribution, he won the 2003 Nobel Prize in Economics. ARCH models expect the change of the current error term or innovation to be a function of the actual sizes of the past time periods’ blunder terms regularly the fluctuation is related to the squares of the previous innovations. In 1986, his doctoral understudy Tim Bollerslev created the Generalized ARCH model abbreviated as GARCH (Bollerslev, 1986). In 1987, Bollerslev suggested that the GARCH model $\varepsilon_t = \sqrt{h_t}\eta_t$ with assumed conditionally normal distribution might not sufficiently cover the leptokurtosis in financial time series. He suggested that sometimes the model $\varepsilon_t = \sqrt{h_t}\eta_t$ has thicker tails and is better described by a student-t distribution. He therefore introduced the GARCH-t model, which assumes a student-t distribution instead of the normal distribution (Bollerslev, 1987). When studying financial time series, most researchers study the return time series rather than the raw price data. In 1997, MacKinlay, Lo and Campbell gave two primary reasons for this. First, the return of resource may be a total, scale free outline of that specific speculation opportunity. Secondly, the return series are much easier to handle than the raw price series since it has more attractive statistical properties (Campbell et al., 1997). There are several different definitions of returns. In this work, the returns of study will be log returns. The variables of interest are daily log returns, r_t, defined by the interdaily difference of the natural logarithm of the daily asset prices, p_t. The daily returns are thus defined by:

$$r_t = log(p_t) - log(p_{t-1}) = log\left(\frac{p_t}{p_{t-1}}\right) \tag{1.1}$$

2. Methodology

2.1 ARMA (m,n)-GARCH(p,q)

In the real world, the return processes may be stationary, so we combine the ARMA model and the GARCH model, where we use ARMA to fit the mean and GARCH to fit the variance.

Let X_t be ARMA(m, n) which refers to the model with m autoregressive terms and n moving average terms and the process $\varepsilon_t = \sqrt{h_t}\eta_t$ be a GARCH(p,q) process:

$$X_t = \mu + \sum_{i=1}^{m} \emptyset_i X_{t-1} - \sum_{j=1}^{n} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$\varepsilon_t = \sqrt{h_t}\eta_t$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_k \varepsilon_{t-k}^2 + \sum_{l=1}^{q} \beta_t h_{t-l}$$

2.1.1 Time Series-ARCH

Let η_t be $\mathcal{N}(0, 1)$. The process $\boldsymbol{\varepsilon_t}$ is an ARCH(p) process if it is stationary and if it satisfies, for all t and some strictly positive-valued process $\sqrt{h_t}$ the equations

$$\varepsilon_t = \sqrt{h_t}\eta_t$$

$$h_t = \alpha_o + \sum_{i=1}^{p} \propto_i \epsilon_{t-i}^2$$

with F_{t-1} is the information set defined by $F_{t-1} = \{\epsilon_{t-j};\ \ j \geq 1\}$

i.e. the σ-algebra generated by the past values of the process $(\epsilon_t)_t$ along with other information available at time t − 1.

Note that η_t can be other white noise, no need to be Gaussian.

2.1.2 GARCH (Generalized ARCH)

ARCH models often require relatively long lags in the conditional variance equations. Four years after the introduction of ARCH, Engle's graduate student Tim Bollerslev addressed this issue with the generalized autoregressive conditional heteroscedasticity (GARCH) model (Bollerslev, 1986).
In GARCH (p,q) models, the conditional variance equation is extended to include q lagged values of the conditional variance.
Let η_t be $\mathcal{N}(0, 1)$. The process ϵ_t is an GARCH (p,q) process if it is stationary and if it satisfies, for all t and some strictly positive-valued process $\sqrt{h_t}$ the equations

$$\epsilon_t = \sqrt{h_t n_t} \tag{2.1}$$
$$h_t = \alpha_o + \sum_{i=1}^{p} \propto_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_t h_{t-j}$$

where $\alpha_o > 0, \alpha_i \geq 0, i = 1, \dots., p,$ and $\beta_j \geq 0, j = 1, \dots \dots, q.$
Using the lag or backshift operator B, the GARCH(p,q) model is:

$$\epsilon_t = \sqrt{h_t n_t}$$
$$h_t = \alpha_o + \alpha(B)\epsilon_t^2 + \beta(B)h_t$$

With $\alpha(B)=\sum_{i=1}^{p} \alpha_i B^i$ and $\beta(B) = \sum_{j=1}^{p} \alpha_j B^j$.

2.1.3 The advantage of GARCH(p,q) models

This allows the entire history of past shocks to influence the current value of the conditional variance. Bollerslev showed a GARCH model with a small number of terms may be more efficient than an ARCH model with many terms.
If all the roots of the polynomial $|1\text{-}\beta(B)| = 0$ lie outside the unit circle, we have:

$$h_t = \alpha_0 + \alpha(B)\epsilon_t^2 + \beta(B)h_t \Rightarrow$$
$$h_t = (1 - \beta(B))^{-1}(\alpha_0 + \alpha(B)\epsilon_t^2)$$
$$= \sum_{k=1}^{\infty} \beta(B)^k (\alpha_0 + \alpha(B)\epsilon_t^2)$$
$$h_t = \alpha_0^* + \sum_{k=1}^{\infty} \psi_k \epsilon_{t-k}^2$$

Which may be seen as an ARCH (∞) process since the conditional variance linearly depends on all previous squared residuals.

2.2 Parameter Estimation

2.2.1 Maximum Likelihood Estimation for GARCH (p,q)

The parameter vector is denoted by θ, that is:

$$\theta = \left(\alpha_0, \alpha_1, \ldots\ldots, \alpha_p, \beta_1, \ldots\ldots, \beta_q\right).$$

We assume that there is a unique stationary solution to the set of equations (2.1).

- For normally distributed standardized innovations: likelihood function for a sample of n observations

$$L_n(\epsilon_t|F_{t-1};\theta) = \prod_{t=1}^{n} \frac{1}{\sqrt{2\pi h_t}} exp\left(-\frac{1}{2}\frac{\epsilon_t^2}{h_t}\right).$$

Log-likelihood function for normally distributed standardized is given by:

$$log(L_n(\epsilon_t \mid F_{t-1};\theta)) = -\frac{n}{2}log(2\pi) - \frac{1}{2}\sum_{t=1}^{n} log(h_t) - \frac{1}{2}\sum_{t=1}^{n}\frac{\epsilon_t^2}{h_t}.$$

Note: cannot minimize the log-likelihood equations analytically. Maximum likelihood estimates of the parameters are obtained by using numerical methods.

- For standardized t-distributed innovations:

Density function of the standardized t-distribution with $\upsilon > 2$ degrees of freedom is given by

$$d(\eta_t;\upsilon) = \frac{\Gamma(\frac{\upsilon+1}{2})}{\Gamma(\frac{\upsilon}{2})\sqrt{\pi(\upsilon-2)}}\ (1+\frac{\eta_t^2}{\upsilon-2})^{-\frac{\upsilon+1}{2}}$$

Where $\Gamma(\upsilon) = \int_0^\infty e^{-x}x^{\upsilon-1}dx$ is the gamma function and is υ is the degree of freedom.

Log-likelihood function for standardized t-distributed is given by:

$$log(L_n(\epsilon_t \mid F_{t-1};\theta)) = n[log\,\Gamma(\frac{\upsilon+1}{2}) - log\,\Gamma(\frac{\upsilon}{2}) - \frac{1}{2}log(\pi(\upsilon-2))]$$

$$-\frac{1}{2}\sum_{t=1}^{n}[log(h_t) + (1+\upsilon)\,log\,(1+\frac{\eta_t^2}{\upsilon-2})]$$

2.3 Building GARCH(p,q) model

In order to build an GARCH(p,q) model it is important to determine the correct number of lags. There are many ways of determining the order and below there is three different information criteria that we use in order to determine the best order for the GARCH(p,q) models.

2.3.1 Determining the order for GARCH(p,q) model

To check if the model is correctly specified, we have two forms to detect the right model. One form is comparing the coefficients of the model. Second form is comparing the value of the log likelihood, the Akaike Information criteria (AIC), Bayesian Information criteria (BIC) and Hannan-Quinn Information Criteria (HQIC). Note that these criteria only compare considered models and selects the model that best fit the given data.

The value of the log likelihood estimates when the model converges, and then is calculated by the following equation:

$$l = -\frac{n}{2}[1 + \log(2\pi) + \log(\frac{\epsilon'\epsilon}{n})$$

Where $\epsilon'\epsilon$ is the sum of the squared residuals of the model, and n is the number of observations. The Akaike Information criteria (AIC), Bayesian Information criteria (BIC) and Hannan-Quinn Information Criteria (HQIC) ensures that the model complies with the condition established for an ARMA model that balances the goodness of fit and parsimonious specification. The formulas to calculate these coefficients are the following:

$$AIC = -\frac{2l}{n} + \frac{2k}{n}$$

$$BIC = -\frac{2l}{n} + \frac{k\log(n)}{n}$$

$$HQIC = -\frac{2l}{n} + \frac{2k\,(\log(n))}{n}$$

Where k is the number of estimated parameters, and l is the value of the log likelihood function using the k estimated parameters. The rule is selecting a particular order k that has the minimum AIC, BIC and HQIC value (Arndt and Arndt, 2001).

2.4 Measuring the Forecast Accuracy

When we have selected number of lags for the best-fitted model of each of the three criteria we use the Root Mean Squared Error (RMSE) of the forecasts to determine which model to choose. This result is then compared with the RMSE result for all models, and the model with the lowest RMSE value will be the best forecasting model for the given data. The RMSE function can be described as:

$$RMSE = \sqrt{\frac{1}{M}\sum_{i=1}^{M}(X_{t+i} - \widehat{X_t}(i))^2}$$

where M is the size of the out-of-sample forecast period and $\widehat{X_t}(i)$ is the predicted value of X_{t+i}.
RMSE is always non negative, and a value of 0 (never achieved in practice) would indicate a perfect fit to the data. In general, a lower RMSE is better than a higher one (Chai and Draxler, 2014).

2.5 Method

The steps used on the following models GARCH with normal innovations and GARCH with student-t innovations to find the best forecast accuracy for the conditional variance are explained below. Remember that the last 25% observations where excluded in order to evaluate the forecasting accuracy of the models. All calculations have been done using the rugarch package in R.

- First, we differentiate the time series using the logarithmic returns to turn the series into a stationary time series.
- The ACF/PACF function and the Lagrange multiplier test were applied to the residuals to examine if there were any ARCH effect.
- Then the maximum likelihood function was estimated for different lags of the GARCH(p,q) models, and the logarithmic value of the result was calculated.
- With different log likelihood values, the AIC, HQIC and the BIC function where evaluated to find the value that minimizes the functions. The selected value then represented the number of lags to choose for the GARCH(p,q) model.
- Then the coefficients for all models where estimated by maximizing the likelihood function for the chosen number of lags.
- Then We estimated the conditional variance. data set.
- Then We calculated the log returns for the remaining 25% observations for each data set.
- And last, we evaluated the forecasting accuracy using the RMSE function.

3. Empirical Analysis and Results

3.1 Summary Statistics and Diagnostic Check

As can be seen in **Figure 1**, there is a general upward trend in the exchange rates over the sample period.

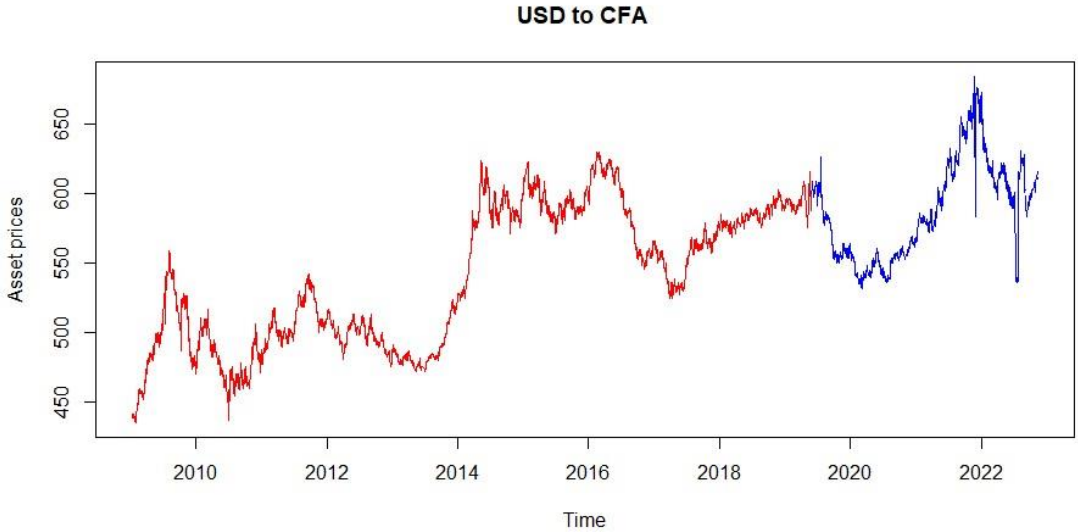

Figure 1: Daily exchange rate of USD to CFA from 13-11-2009 until 18-09-2023. In total there are 5058 observations. The red line represents the exchange rate during the in-sample period and the blue line represents the exchange rate during the out-of-sample period.

The main variable of study as mentioned is not the price process but the daily log return defined in equation (1.1). The **Figure 2** shows the daily return for the in-sample period. The daily return series seems to be a stationary process with a mean close to zero and the plot also reveals that the variances change over time and volatility tends to be cluster, which is a sign of ARCH effect and there are periods with high volatility and periods with low volatility.

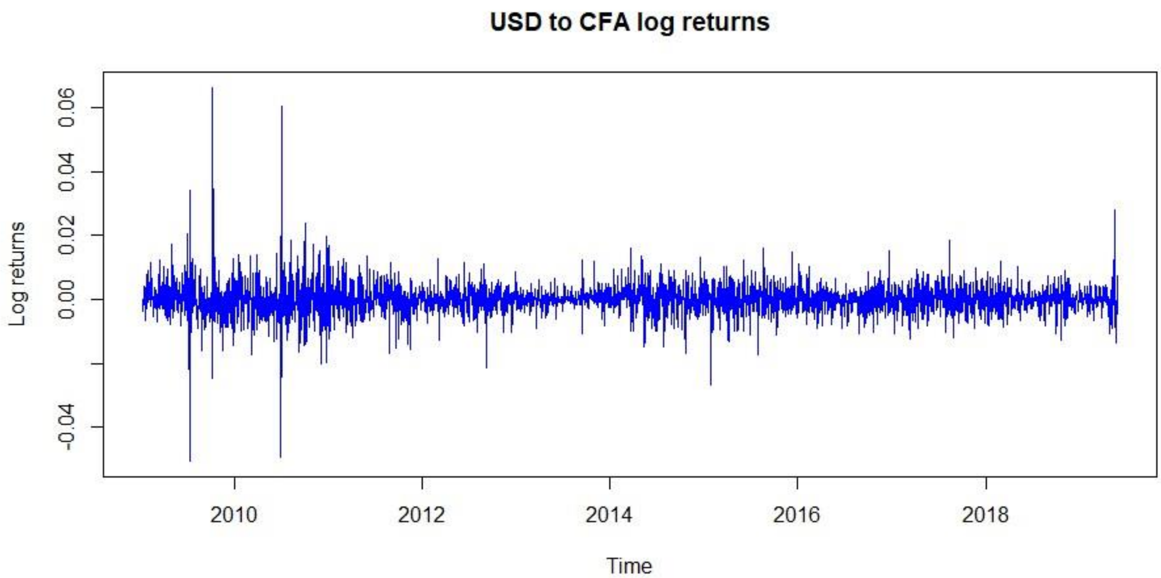

Figure 2: Daily log returns of exchange rate of USD to CFA from 13-11-2009 until 01-03-2020, which is the in-sample period consisting of 3793 observations.

In this study, the time series data is employed. One key assumption in empirical work based on time arrangement information is that the basic time arrangement is feebly stationary, which is both the cruel of r_t and the covariance between r_t and r_{t-h} are time invariant, where h is an arbitrary integer. In any case, numerous ponders have found that larger part of time arrangement factors are non-stationary and utilizing non-stationary time arrangement in a relapse examination may lead to spurious relapse. Consequently, sometime recently doing any observational investigation, we ought to check the stationarity suspicion to begin with. Among a number of unit root tests accessible for stationarity investigation, Increased Dickey-Fuller (ADF test) and Philip-Perron (PP) test are most prevalent utilized by analysts. In this study, Dickey-Fuller test (ADFtest) are utilized to test the stationarity of the trade rate arrangement and the log return arrangement. Results in **Table 1** appear that stationary presence within the to begin with contrast arrangement (i.e. log return series) at 1% significant level with p-values of 0.01. **Table 1** reports the summary statistics for the daily exchange rate return series. The exchange rate return series are positively skewed, and have extremely fat tails (kurtosis > 3). This indicates a departure from normality, which is also confirmed by the quantile-quantile plot in Figure 3 and by Jarque- Bera test (JB test). Result of JB test is shown in **Table 1**, indicating that the null hypothesis of normal distribution for daily exchange rate returns is rejected at 1% significant level.

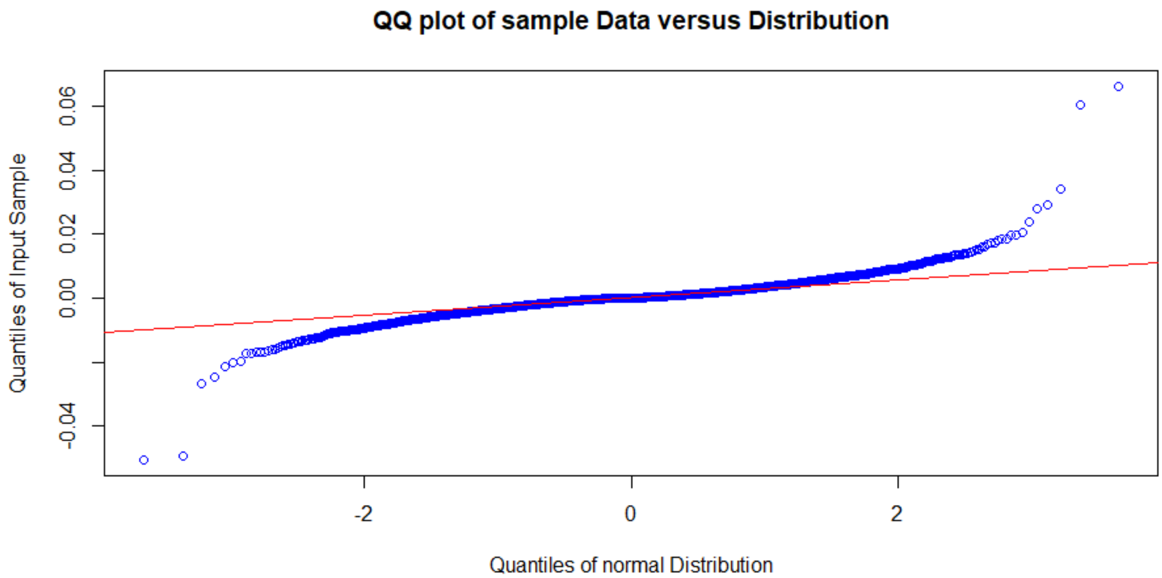

Figure 3: QQ plot of log returns exchange rate of the in-sample period.

For model selection, Ljung-Box (LB) test with 15 df is conducted to check whether AR and ARCH effects exist. For AR effects, the null hypothesis of the test is Ho: p1 = …= pm = 0 where p is the direct relationship between serial every day log returns. For Curve impacts, the invalid speculation is the same, separated from that p is the direct relationship between serial squared log returns. The significance level of 5% is used for the two tests. P-values and test statistics of the two tests are summarized in **Table 1**.

All p-value of LB test for log return series and squared log returns are less than 0.01 indicating the null is rejected at 1% significant level. Consequently, AR and ARCH effects do exist in these series. This is also confirmed by the autocorrelation and partial autocorrelation plot of returns and squared returns in Figure 4.

The sample ACF is a tool for estimating the dependence in the data. For example, if the sample ACF is close to zero we might suggest that it is iid noise (Brockwell and Davis, 2013). Also, the PACF could be used in order to determine the order of the ARCH (p) model (Graves, 2012).

The Lagrange multiplier test for the Autoregressive heteroscedasticity (ARCH) effect was done for all residuals up to lag 30. If the LM test is not rejected, i.e. p-value exceeds 5%, then the null hypothesis that all coefficients in the ARCH model are zero, cannot be rejected and we say there is no ARCH effect (Engle,1982). LM test for the ARCH effect was carried out and it was found that the null hypothesis is rejected for all lags, all p-values are less than 0.05, so we have ARCH effect. As a consequence, taking the AR effects and ARCH effects into consideration, ARMA-GARCH models are used in this study.

Table 1: Summary of descriptive statistics and diagnostic check of Exchange rate and returns series of USD to CFA franc Statitics USD Vs CFA

Statitics	USD Vs CFA	
	p_t during the entire study period	r_t for the in-sample period
Size	5058	3792
MEAN	551.17	0
Std.Dev	50.74	0
MAXIMUM	684.19	0.07
MINIMUM	434.67	-0.05
Skewness	-0.13	0.8
Kurtosis	-0.96	27.7
J-Bera test	$207.01(< 2.2e-16)**$	$121739(< 2.2e-16)**$
ADFtest	$-3.1751(0.09215)$	$-15.34(0.01)*$
LB-Q(15) test	$73250(< 2.2e-16)**$	$55260(4.794e-07)**$
LB-Q$(15)^2$ test	$73186(< 2.2e-16)**$	$55294(< 2.2e-16)**$

Note : p-values are in parentheses, ** indicates significant at 1%, * indicates significant at 5%.

Table 1 shows some statistical information about the logarithmic return series. The series to be normal distributed its kurtosis must be three (Shumway and Stoffer, 2006) and as we can see the logarithmic return series seems to not be normally distributed.

3.2 Model Estimation

According to **Figure 4,** the ACF and PACF correlograms of log returns and squared log returns of exchange rate show cuts off at lag three. The autocorrelation and partial autocorrelation coefficients are equally likely to be positive or negative from one lag to another. Since both ACF and PACF for the log returns and squared log returns of exchange rates die away through different lags, both autoregressive and moving average (ARMA) model are included.

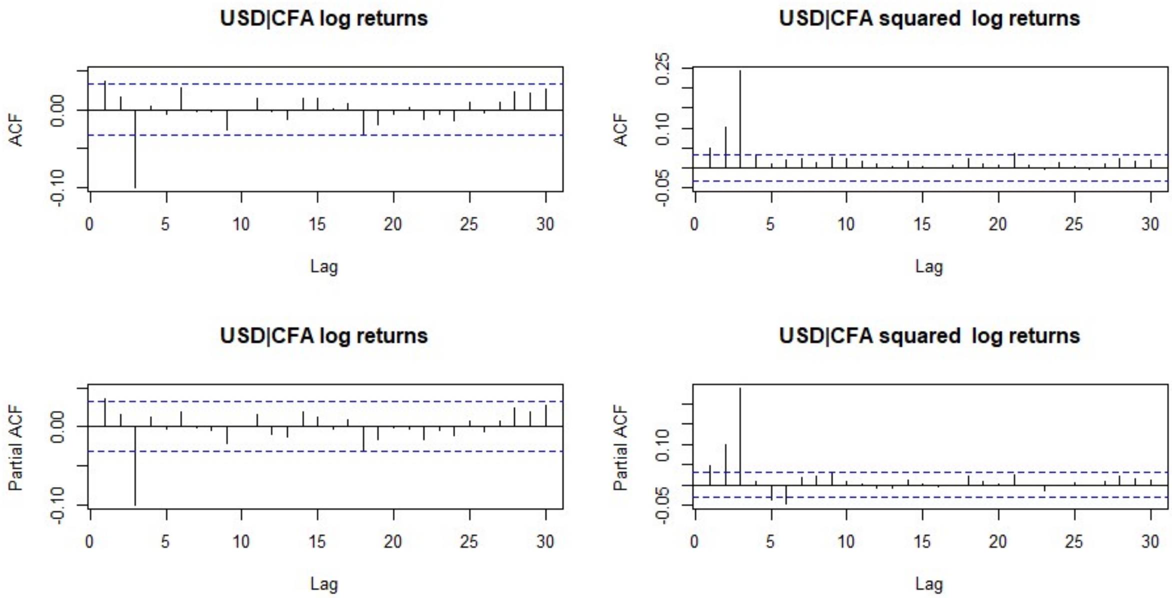

Figure 4: Autocorrelation and partial autocorrelation of log returns and squared log returns.

As shown in **Figure 4**, significant serial correlations do exist in the first 10 lags of the series. In this study, ARMA(3,1) specification is chosen to reflect the autocorrelation in the return series as supported by the ACF and PACF correlograms of log returns and squared log returns of exchange rate, auto.arima and the principle of parsimony which is the rule that seek simplest model as much as possible. Therefore, an ARMA (3,1) model is selected to fit the mean of exchange rate returns series. Additionally, as proven above, normality is rejected in exchange rate return series, therefore Student-t error distribution is employed in this study when specifying GARCH models. The order of GARCH models are determined based on information criteria AIC, HQIC and the BIC. The rule is selecting particular order k that has the minimum AIC, HQIC and the BIC value.
ARMA (m,n)- GARCH(p,q) processus:

$$X_t = \mu + \sum_{i=1}^{m} \emptyset_i X_{t-1} - \sum_{j=1}^{n} \theta_j \varepsilon_{t-j} + \varepsilon_t$$

$$\epsilon_t = \sqrt{h_t \eta_t}$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_k \varepsilon_{t-k}^2 + \sum_{l=1}^{q} \beta_t h_{t-l}$$

Where n_t is the white noise which can be normally or student's t-distributed.

Table 2: Parameter estimate of the model with different distributed

	ARMA(3,1)–GARCH(1,1)		ARMA(3,1)–GARCH(2,1)		ARMA(3,1)–GARCH(1,2)	
	Normal	Student	Normal	Student	Normal	Student
μ	0.000042	0.000086	0.000047	0.000087	0.000042	0.000083
ϕ_1	0.301459	0.495843	0.312132	0.530387	0.335659	0.504143
ϕ_2	0.061914	0.034962	0.062191	0.035451	0.061652	0.035893
ϕ_3	-0.054890	-0.053062	-0.057356	-0.054503	-0.057879	-0.051461
θ_1	-0.287708	-0.451075	-0.298235	-0.487598	-0.318524	-0.461514
α_0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
α_1	0.052476	0.020316	0.054837	0.018961	0.073239	0.033911
α_2			0.000079	0.000000		
β_1	0.943304	0.978604	0.940406	0.980039	0.589433	0.345806
β_2					0.330138	0.619226
shape		3.249188		3.278141		3.193115
LogL.hood	15406.65	15790.34	15406.75	15790.17	15410.09	15792.49
AIC	-8.1217	-8.3235	-8.1212	-8.3229	-8.1229	-8.3241
BIC	-8.1085	-8.3087	-8.1064	-8.30646	-8.1081	-8.3076
HQIC	-8.1170	-8.3182	-8.1159	-8.3170	-8.1177	-8.3192
LB lag[1]	(0.4971)	(0.2751)	(0.4990)	(0.3298)	(0.6214)	(0.3691)
LM lag[8]	(0.008976)	(1.782e-10)	(0.2619)	(0.7435)	(0.2908)	(0.7214)
RMSE	0.003586253	0.003588165	0.003586099	0.003587204	0.003585635	0.003584048

Note : p-values are in parentheses and the colored cell indicates best value.

3.2.1 In-sample estimation accuracy

To check whether the accuracy of volatility forecasting among the different models varied with distribution assumptions, we compared the log-likelihood, Hannan-Quinn Information Criteria (HQIC), Bayesian information criterion (BIC), and Akaike information criterion (AIC) for all of the models, estimating for whole-sample observations under normal and Student's t-distribution. **Table 2** shows the results. It is clear that the performance and goodness of fit of each model improved when Student's t-distribution was used for the residuals. Considering the Student's t-distribution for the residuals and the comparison of indicators reveals that among all of the models used for in-sample estimation, ARMA(3,1)–GARCH(1,2) is the best since it has the highest maximum likelihood and the lowest HQIC and AIC.

3.2.2 Out-of-sample forecasting accuracy

To check the determining precision of the models, we made a pseudo test utilizing the period from 02-03-2020 to 18-09-2023. All of the models were estimated for the pseudo sample period. The forecasting performance of the models was compared on the basis of one indicator under normal distribution and Student's t-distribution: root mean square error (RMSE). **Table 2** shows the comparative forecasting accuracy of the different models under normal and Student's t-distribution for the residuals. For the ARMA(3,1)–GARCH(1,2), which had the best in-sample estimation accuracy under Student's t-distribution, showed also the highest accuracy when such distribution was used for out-of-sample forecasting.

4. Conclusions

This study investigates the nature of volatility of CFA exchange rate in term of US dollar through using the combination of ARMA(3,1) with GARCH(1,1), GARCH(1,2) and GARCH(2,1) models with assumption of normal and Student's t-distribution. Results show that the combination of linear and non-linear model in this study well capture volatility dynamics of CFA exchange rate in term of US dollar series, whereas the mean equations are reasonably adequate to capture the mean return series. Moreover, results found that model specification with Student's t-distribution is a better choice than Gaussian distribution assumption as it well captures non-normality of the series. Further, in-sample estimation accuracy was observed to be improved when such a distribution was used. For modeling in-sample volatility dynamics, ARMA(3,1)–GARCH(1,2) with assumption of Student's t-distribution was found to be the most accurate. In terms of out-of-sample forecasting accuracy, ARMA(3,1)–GARCH(1,2) with assumption of Student's t-distribution also is considered as the best model since RSME was observed to be the lowest for all models.

Overall findings suggest that considering a particular class of GARCH models such as Exponential GARCH, Integrated GARCH, Fractionally IGARCH, Threshold GARCH, Asymmetric Power ARCH,… such an approach can create a more adaptable lesson of forms for the conditional fluctuation that are competent of clarifying CFA trade rate in term of US dollar instability in a much superior way than institutionalized GARCH models but it is past the scope of this ponder. Therefore, further studies about Modeling and forecasting exchange rate volatility in WAEMU are still necessary to obtain a better understanding of it. In general, this research gives a recommendation to different researchers to do further studies on Modeling and forecasting exchange rate volatility in Africa, considering this as a baseline.

References

[1] Paul De Grauwe (1988). Exchange rate variability and the slowdown in growth of international trade. Staff Papers, 35(1): 63-84.

[2] Andrew K. Rose (2000). One money, one market: the effect of common currencies on trade. Economic policy, 15 (30): 08-45.

[3] Girum T.Z. and Didier D. and Ntwali M.P. (2014). Time series analysis on monthly average Rwanda currency exchange rate against us dollars. Journal of Business and Economic Management, pages 2(5): 074-083.

[4] Carmen M. Reinhart and Kenneth S. Rogoff (2004). The modern history of exchange rate arrangements: a reinterpretation. the Quarterly Journal of economics, 119(1): 1-48.

[5] Richard N. Cooper. (2014). Exchange rate choices. https://dash.harvard.edu/handle/1/34307223.

[6] Jeffry A. Frieden (2016). Currency politics: The political economy of exchange rate policy. Princeton University Press.

[7] Mark J. Flannery and Christopher M James (1984). Market evidence on the effective maturity of bank assets and liabilities. Journal of Money, Credit and Banking, 16(4): 435-445.

[8] Robert F. Engle (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica: Journal of the Econometric Society, pages 987-1007.

[9] Tim Bollerslev (1986). Generalized autoregressive conditional heteroskedasticity. Journal of econometrics, 31(3): 307-327.

[10] Tim Bollerslev (1987). A conditionally heteroskedastic time series model for speculative prices and rates of return. The review of economics and statistics, pages 542-547.

[11] John Y Campbell, Andrew W Lo and Archie Craig MacKinlay (1997). The econometrics of financial markets, volume 2. Princeton University press Princeton, NJ.

[12] Christoph Arndt and Christoph Arndt (2001). Akaike’s information criterion. Information Measures: Information and Its Description in Science and Engineering, pages 347-361.

[13] Tianfeng Chai and Roland R Draxler (2014). Root mean square error (rmse) or mean absolute error (mae). Geoscientific model development discussions, 7(1) :1525–1534.

[14] Peter J. Brockwell and Richard A. Davis (2013). Time series: theory and methods. Springer Science & Business Media.

[15] Graves S. (2012). Fints: Companion to tsay (2005) analysis of financial time series. R package version 0.4-4.

[16] Robert H Shumway and David S Stoffer. (2006). Time series regression and exploratory data analysis. Time Series Analysis and Its Applications: With R Examples, pages 48-83.