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Modeling exchange rate volatility, using Univariate Generalized Autoregressive conditionally Hetroscedastic type models: evidence from Afghanistan

Mahmood Mahroowal[1], Hedayatullah Salari[2]

[1,2]Paktia University, Paktia, Afghanistan

Correspondent author: mahmood_w@yahoo.com **DOI 10.31150/ajebm.Vol2.Iss3.82**

Abstract: In this study, an attempt is made to examine the performance of GARCH family models (including symmetric GARCH,GARCH-M, and asymmetric EGARCH models) in Forecasting the volatility behavior of Afghanistan foreign exchange rate. Daily foreign exchange rates of Afghani with USD data, ranging from 2018/09/01 to 2019/10/16 are used. Theoretically, the first order autoregressive behavior of the foreign exchange rate was evidenced in GARCH, GARCH-M and E-GARCH models while GARCH, GARCH-M and E-GARCH models support that previous day foreign exchange rate affected the current day exchange rate. Based on the comparison of the above models, found the GARCH (1,1) is the best model to explain the volatility of the return on the exchange of AFN with US Dollar.

Keywords: Exchange rate, volatility, GARCH models, Afghanistan.

Introduction

To know the extent of transaction exchange risk, understanding exchange rate volatility is very important. The wider the conditional distribution of future exchange rates the higher is risk; and the width of the distribution in turn depends on the volatility or standard deviation of changes in exchange rates. Many financial researchers have spent considerable computer time examining exchange rate data, and they have come to the conclusion that exchange rate volatility is not constant over time. In fact, as is true for the returns on many assets, percentage changes in exchange rates show a pattern known as volatility clustering. When volatility is high it trend to remain high for a while; periods of low volatility are likewise persistent. Asset market in general and the foreign exchange market in particular, appears to go through periods of tranquility and periods of turbulence.

Traditionally, corporate decision makers use volatility models as a tool in portfolio allocation, risk management and as an input in derivative asset pricing while the policymakers use the same to keep an eye on the economic factors, their impact on exchange rate, and to develop monetary and fiscal policies as well. Export oriented countries with substantial impact of exports on economic growth emphasize more on the exchange rate volatility in their economic policies. Many financial crises stemming from sudden and unexpected oscillation in the financial crises of Latin American, Southeast Asian and Russian economies highlighted the importance of measurement of foreign exchange rate volatility, its forecasting and its behavior. Foreign exchange rate system can either be fixed or floating, that is, fixed exchange rates is treated as a permanent one and the floating exchange rate may drift, up and down, according to certain market trends. Floating Foreign exchange rates are expected to be more volatile as they are free to fluctuate. The volatility in Foreign exchange rates result in increase of exchange rate risk and adversely affects the international trade and investment decisions.

The purpose of the current study is to model and quantify the volatility of exchange rate of Afghani (AFN) against the US Dollar through different available types of GARCH family models. The symmetric GARCH (1,1), GARCH-M (1, 1) and asymmetric EGARCH (1, 1) models are applied to capture the main characteristics of exchange rate, such as, volatility clustering and the leverage effect. The objective of the paper is to estimate the time varying variances in Afghan-US Foreign exchange rate, from year 2018/09/01 to 2019/10/16, through GARCH (1, 1), EGARCH (1, 1) and M-GARCH (1, 1) models

Foreign exchange rate volatility is an important factor involved in the decision making of investors and policy makers. The current study is an attempt in Afghanistan to capture the Afghani (AFN) volatility against US Dollar.

Kamal Yasir et al (2012) examined the performance of GARCH family models (including symmetric GARCH-M, asymmetric EGARCH and TARCH models) in forecasting the volatility behavior of Pakistani FOREX market. Theoretically, the first order autoregressive behavior of the FOREX rate was evidenced in GARCH-M and E-GARCH models while the GARCH-M model supports that previous day FOREX rate affected the current day exchange rate. The EGARCH-based evaluation of FOREX rates showed asymmetric behavior of volatility, where

TARCH model showed insignificance but they stated that detailed exploratory analysis of the FOREX rate behavior requires prolonged study by applying advance models.

S. Aun Hassan (2012) focused on persistence and asymmetry in volatility of major exchange rates due to exogenous shocks. The paper employed a univariate GARCH and an EGRACH model to test the persistence and asymmetry of exchange rate volatility using data from the past decade plus. his results showed high persistence and asymmetric behavior in volatility implying that the effect of good news on exchange rates is different from the effect of bad news. He stated the results of this paper have important implications for foreign exchange investors and will provide a better understanding of the foreign exchange market to interested observers.

According to the findings of Taylor (2005), foreign exchange volatility inputs are supportive in certain financial decisions related to portfolio optimization, hedging, risk management, pricing of options and other types of derivatives. Foreign exchange rate is one of the key macroeconomic variables, with direct effect on international trade balance.

Alberg et al. (2006) investigated the forecasting performance of GARCH, EGARCH, GJR and APARCH models and found that the EGARCH model, which used a skewed Student-t distribution, produced significant results than any other model.

Hsieh (1989) used 10 years (1974 – 1983) of daily closing-bid prices, consisting of 2,510 observations, for five countries in comparison of US dollar to estimate the autoregressive conditionally heteroscedastic (ARCH) and generalized autoregressive conditionally heteroscedastic (GARCH) models along with the other modified/altered types of ARCH and GARCH. The findings of Hsieh (1989) proved that the two understudy models were capable of removing all heteroscedasticity in price changes. It was also concluded that the standardized residuals from all the ARCH and GARCH models using the standard normal density were highly leptokurtic, and the standard GARCH (1,1) and EGACH (1,1) were found to be more efficient for removing conditional heteroscedasticity from daily exchange rate movements. The EGARCH proved to fit the data, better than GARCH model, using a variety of diagnostic checks.

Chao Wei Chong et al (2002) in their study stated within sample estimation results support the usefulness of the GARCH models and reject the constant variance model, at least within-sample. The Q-statistic and LM tests suggest that long memory GARCH models should be used instead of the short-term memory and high order ARCH model. The stationary GARCH-M outperforms other

GARCH models in out-of-sample and one-step-ahead forecasting. When using random walk model as the naive benchmark, all GARCH models outperform this model in forecasting the volatility of the RM/Sterling exchange rates.

Methodology

In the literature most used and simple model is the GARCH (1, 1) process, for which the conditional variance can be written as follows:

Mean equation

$$r_t = \mu + \varepsilon_t$$

Variance equation

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{2-1}^2 + \beta_1 \sigma_{t-1}^2$$

Where $\omega > 0$, $\alpha_1 \geq 0$ and$\beta_1 \geq 0$, and:

r_t = return of the exchange rate at time t,

μ = average return,

ε_t = residual returns, defined as:

$\varepsilon_t = \sigma_t Z_t$

Where Z_t are standardized residual returns (i.e. realization of an iid random variable with zero mean and variance 1), and σ_t^2 stands for the conditional variance. For GARCH (1, 1), the constraints $\alpha_1 \geq 0$ and $\beta_1 \geq 0$ are needed to ensure that σ_t^2 is strictly positive. The conditional variance equation models the time varying nature of volatility of the residuals generated from the mean equation. This specification is often interpreted in a financial context, where an agent or trader predicts this period's variance by forming a weighted average of a long term average (the constant), the forecast variance from last period (the GARCH term), and information about volatility observed in the previous period (the ARCH term). If the asset return was unexpectedly large in either the upward or the downward direction, then the trader will increase the estimate of the variance for the next period, while the GARCH-term generates persistence of volatility.

GRASH-M

The following model is an extension of the basic GARCH framework which allows the conditional mean of a sequence to depend on its conditional variance or standard deviation. A simple GARCH -M (1, 1) model can be written as:

Mean equation

$$r_t = \mu + \lambda \sigma_t^2 + \varepsilon_t$$

Variance equation

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{2-1}^2 + \beta_1 \sigma_{t-1}^2$$

The parameter λ in the mean equation is called the risk premium parameter. A positive λ indicates that the return is positively related to its volatility. In other words, a rise in mean return is caused by an increase in conditional variance as a proxy of increased risk. Engle, Lilien, and Robins assume that the risk premium is an increasing function of the conditional variance of ε_t; in other words, the greater the conditional variance of returns, the greater the compensation necessary to induce the agent to hold the asset (Walter Enders 2010).

Asymmetric GARCH Models

An interesting feature of asset prices is that bad news seems to have a more pronounced effect on volatility than do good news. For many stocks, there is a strong negative correlation between the current return and the future volatility. The tendency for volatility to decline when returns rise and to rise when returns fall is often called the leverage effect (Enders, 2010). The main drawback of symmetric GARCH models is that the conditional variance is unable to respond asymmetrically to rises and falls in ε_t, and such effects are believed to be important in the behavior of stock returns. In the linear GARCH (p,q) model the conditional variance is a function of past conditional variances and squared innovations; therefore, the sign of returns cannot affect the volatilities. Consequently, the symmetric GARCH models described above cannot account for the leverage effect observed in stock returns, consequently, a number of models have been introduced to deal with this phenomenon. These models are called asymmetric models. This paper uses EGARCH for capturing the asymmetric phenomena.

The Exponential Generalized Autoregressive Conditional Heteroscedastic (EGARCH) Model

This model captures asymmetric responses of the time-varying variance to shocks and, at the same time, ensures that the variance is always positive. It was developed with the following simple specification:

$$Ln\,(\sigma_t^2) = \omega + \beta_1 Ln\,(\sigma_{t-1}^2) + \alpha_1 \left\{ \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} - \sqrt{\frac{2}{\Pi}} \right| \right\} - \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

Where γ is the asymmetric response parameter or leverage parameter. The sign of γ is expected to be positive in most empirical cases so that a negative shock increases future volatility or uncertainty while a positive shock eases the effect on future uncertainty.

Data and Empirical Results

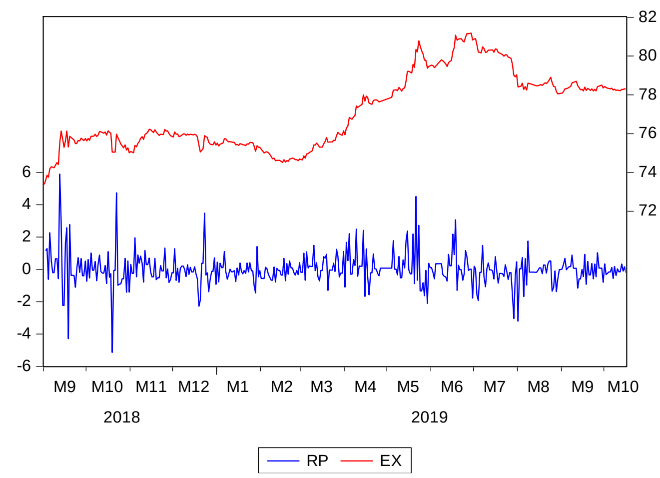
The time series data used for modelling volatility in this paper are the daily average foreign exchange rates of Afghani (AFN) with USD data, ranging from 2018/09/01 to 2019/10/16 is used. Data was taken from Da Afghanistan Bank website. daily returns r_t were calculated as the continuously compounded returns corresponding to the first difference in logarithms of closing prices of successive days:

$$r_t = Log[\frac{P_t}{P_{t-1}}]$$

Where P_t and P_{t-1} denote the closing price of exchange rate of AFN/US at the current (t) and previous day (t-1), respectively.

Because return are too small so to enlarge it, the [return (r)*100] and it is named (RP), in following Graph the Exchange rate of AFN/USD is shown by (EX) and the return is shown by [RP] is plotted.

Graph 1. The Exchange rate of AFN/USD



Return time series Graph show high volatility for some periods and for some period's low volatility. There is a period when volatility is high there is before a period when volatility is high and vice versa. It shows the time series of returns are conditionally heteroskedastic. There are some periods of high variance and some of low variance. There is volatility clustering.

Table 1. Descriptive statistics of returns (RP)

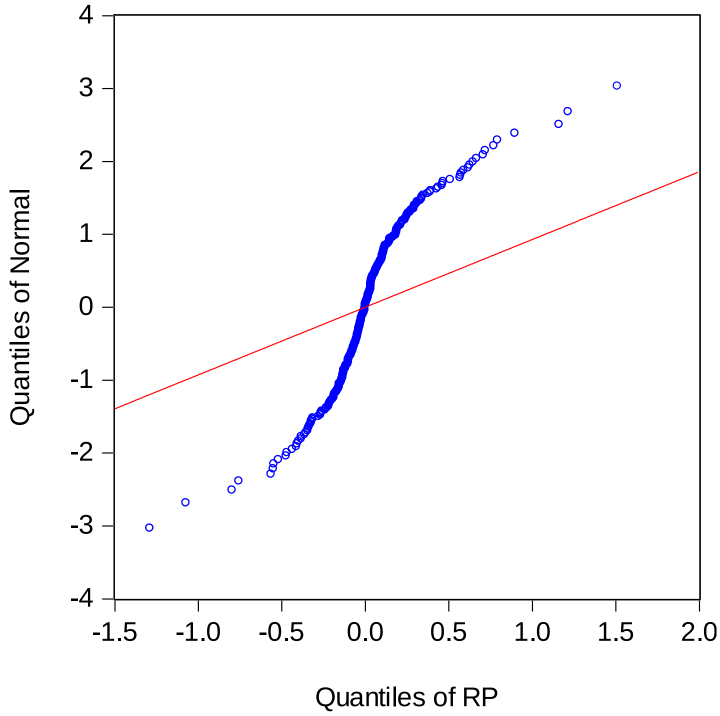
Descriptive statistics of returns (RP)	
Mean	0.015788
Median	0.000000

Maximum	1.509370
Minimum	-1.288902
Std. Dev.	0.253623
Skewness	0.747626
Kurtosis	10.69705
Jarque-Bera	1050.290
Probability	0.000000
Sum	6.472886
Sum Sq. Dev.	26.30875
Observations	410

Table 1 summarizes descriptive statistics of return (rp) have positive skewness and high positive kurtosis. These values signify that the distributions of the series have a long left tail and leptokurtic. Jarque-Bera (JB) statistics reject the null hypothesis of normal distribution at the all conventional level of significance for the variable.

As a further instrument for analyzing the distributional properties, we apply the Q-Q graphical examination to check whether the returns (rp) series are normally distributed. The Q-Q p plot is a scatter plot of the empirical quantiles (vertical axis) against the theoretical quantiles (horizontal axis) of a given distribution (Alexander, 2001). If the sample observations follow approximately a normal distribution with mean equal to the empirical mean (μ) and standard deviation equal to the empirical standard deviation (σ), then the resulting plot should be roughly scattered around the 45-degree line with a positive slope. The greater the departure from this line, the greater the evidence against the null hypothesis of a normal distribution. The results of this graphical examination are provided in Figure.

Graph 2. The QQ-plot



The QQ-plot in Figure confirms the findings from Table that the returns (rp) data do not follow a distribution similar to a normal distribution.

Augmented Dickey-Fuller (ADF) test results and concludes that return (RP) is stationary. To investigate whether the daily returns are stationary series, the Augmented Dickey–Fuller (ADF) test has been applied. Thereby, the lag length has been selected automatically based on the Schwarz information criterion with a preset maximum lag length of 17. The results are reported as below:

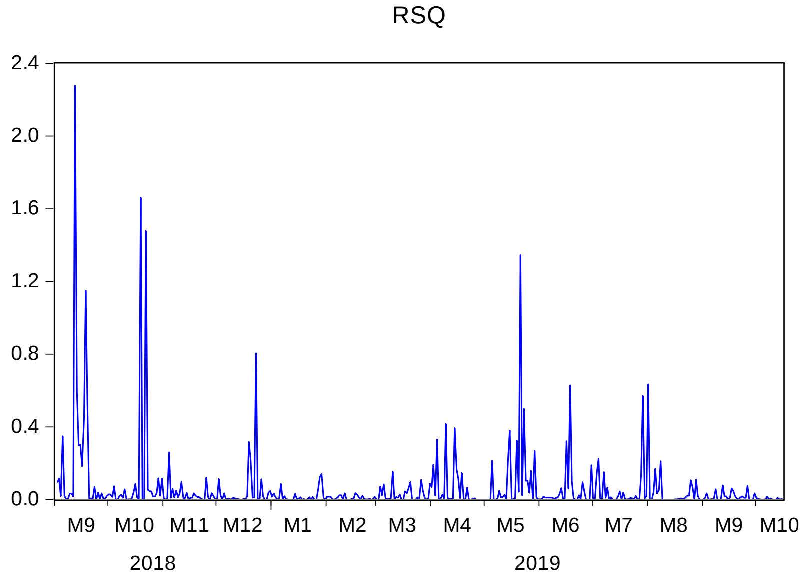
Table 2. ADF unit root test on daily exchange rate returns.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.49498	0.0000
Test critical values:	1% level	-3.446201	
	5% level	-2.868422	
	10% level	-2.570501	

*MacKinnon (1996) one-sided p-values.

As the P-value is significant at conventional level of significance that is meaning data is stationary at level.

Graph 3. Graph of RSQ



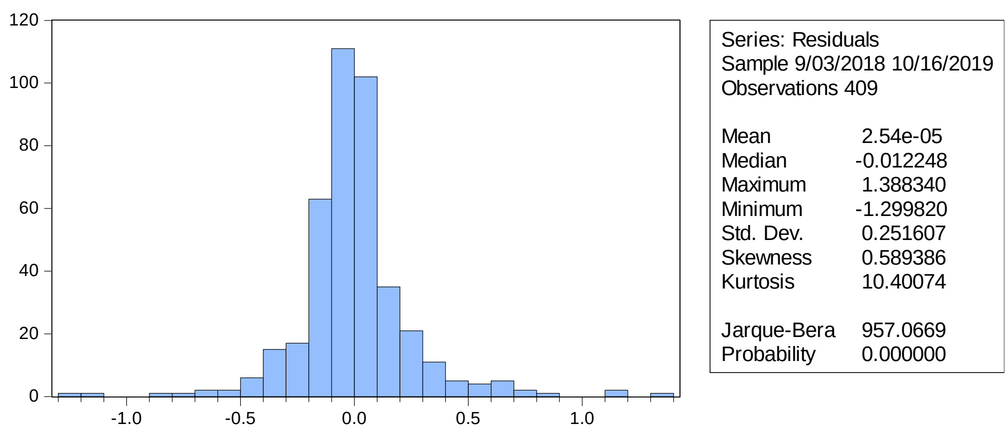
The rp*rp = RSQ is calculated and it is shown for clustering and volatility in the above Graph.

Table 3. The ARMA(1,1) Heteroskedasticity Test: ARCH

Heteroskedasticity Test: ARCH			
F-statistic	5.959630	Prob. F(1,406)	0.0151
Obs*R-squared	5.902348	Prob. Chi-Square(1)	0.0151

The ARMA(1,1) model daily exchange returns (RP) is modeled. The ARCH-LM test results in Table provide strong evidence for rejecting the null hypothesis. Rejecting H0 is an indication of the existence of ARCH effects in the residuals series of the mean equation and therefore the variance of the returns series of AFN/USD is non-constant. So the GARCH models can be used for modeling exchange rate volatility.

Graph 4. Histogram – Narmality test.



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The result of Normality test show it is not Normal distributed.

Table 4. Results of GARCH (1,1) model on daily exchange rate returns.

Variable	Coefficient	Std. Error	z-Statistic	Prob.
		Mean Equation		
C	0.011400	0.011922	0.956143	0.3390
		Variance Equation		
C	0.006052	0.000972	6.224646	0.0000
RESID(-1)^2	0.258794	0.044340	5.836559	0.0000
GARCH(-1)	0.691349	0.030412	22.73312	0.0000

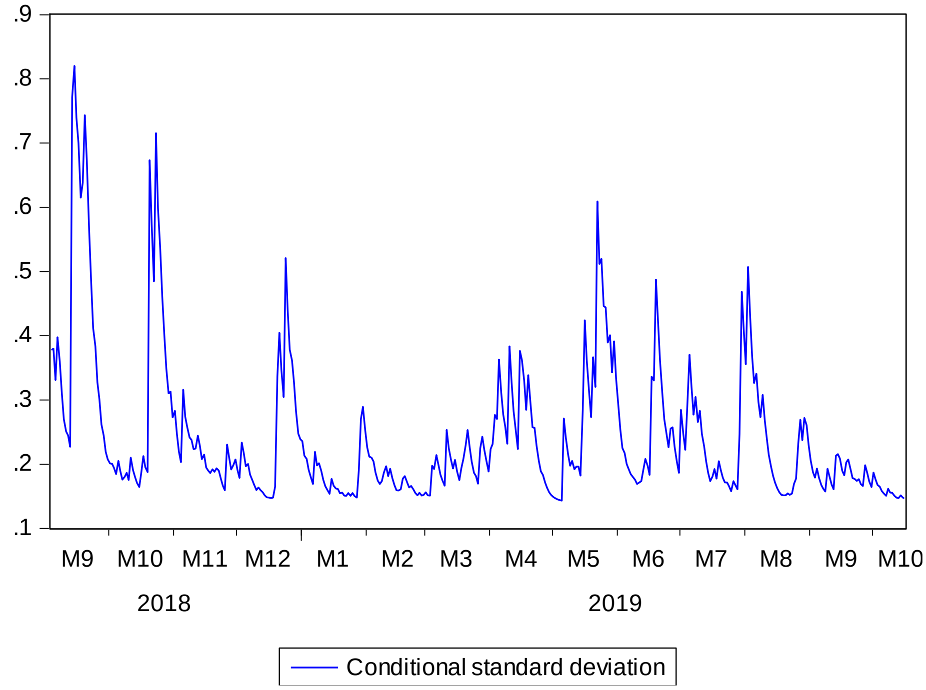
Revenue increased ARCH (-1) or RESID (-1) ^ 2 and GARCH (-1) is equal to 0.950143. Both coefficients α and β models are close to one and significant at the conventional significance level. This shows the exchange rate returns in the one currency is not easy to drop when increasing returns in the long run. GARCH (-1) is positive means the effect of the last news on volatility is significant. The magnitude of the coefficient GARCH (-1) indicated the long memory of the variance.

Table 5. GARCH (1,1) Heteroskedasticity Test: ARCH

Heteroskedasticity Test: ARCH			
F-statistic	0.008904	Prob. F(1,406)	0.9249
Obs*R-squared	0.008948	Prob. Chi-Square(1)	0.9246

The ARCH-LM test results in Table provide strong evidence of accepting the null hypothesis. Acceptting H0 is an indication of no existence of ARCH effects in the residuals series of the mean equation and therefore the variance of the returns series of is constant.

Graph 5. GARCH graph



The GARCH graph result show the Afghani exchange rate with USD is not risky currently.

Table 6. Results of GARCH-M model on daily exchange rate returns.

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Mean Equation				
@SQRT(GARCH)	-0.152194	0.179029	-0.850110	0.3953
C	0.041463	0.036819	1.126109	0.2601
Variance Equation				
C	0.005899	0.000958	6.155923	0.0000
RESID(-1)^2	0.266918	0.048287	5.527765	0.0000
GARCH(-1)	0.689322	0.033497	20.57881	0.0000

The sum of the variable ARCH (-1) and GARCH (-1) equals 0.95624. It shows the rate of return does not go down when increasing returns in the long term. The coefficients of the GARCH (-1) is positive and less than one, meaning that the effects last news on volatility is significant. The magnitude of the coefficient GARCH (-1) indicated the long memory of the variance. For the mean equation, the coefficient of the risk premium is not significant. It showed no statistical evidence that the increased risk might cause an increase in returns.

Table 7. GARCH-M Heteroskedasticity Test: ARCH

Heteroskedasticity Test: ARCH			
F-statistic	0.123731	Prob. F(1,407)	0.7252
Obs*R-squared	0.124301	Prob. Chi-Square(1)	0.7244

The ARCH-LM test results in Table provide strong evidence for accepting the null hypothesis. accepting H0 is an indication of the no existence of ARCH effects in the residuals series of the mean equation and therefore the variance of the returns series is constant.

Table 8. Results of EGARCH model on daily exchange rate returns (RP).

Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
Mean Equation				
C	0.008018	0.058760	-1.422052	0.1550
Variance Equation				
C(2)	-0.714527	0.108892	-6.561773	0.0000
C(3)	0.464841	0.061709	7.532793	0.0000
C(4)	-0.012545	0.035489	-0.353496	0.7237
C(5)	0.862798	0.027191	31.73140	0.0000

The sign of C(5) is positive and significant indicates that a negative shock increases future volatility or uncertainty while a positive shock eases the effect on future uncertainty.

Table 9. EGARCH Heteroskedasticity Test: ARCH

Heteroskedasticity Test: ARCH			
F-statistic	0.237093	Prob. F(1,407)	0.6266
Obs*R-squared	0.238119	Prob. Chi-Square(1)	0.6256

The ARCH-LM test results in Table provide evidence for accepting the null hypothesis at 10% level of significance. Accepting H0 is an indication of doesn't existence of the ARCH effects in the residuals series of the mean equation and therefore the variance of the returns series of is constant.

Coefficients	**GARCH (1, 1)**	**E- GARCH (1, 1)**	**GARCH-M (1, 1)**
	Mean Equation		
Constant	0.011400	0.008018	0.041463
	Variance Equantion		
Constant	0.006052*	-0.714527*	0.005899*
ARCH term	0.258794*	-0.012545	0.266918*
GARCH term	0.691349*	0.862798*	0.689322*
α +β	0.950143	0.850253	0.95624
Log likelihood	22.20295	25.93463	22.64451
	ARCH-LM test for heteroscedasticity		
F-statistic	0.008904	0.163300	0.123731
Prob. F(1,406)	0.9249	0.6863	0.7252
Obs*R-squared	0.008948	0.164038	0.124301
Prob. Chi-Square(1)	0.9246	0.6855	0.7244

Table 10. Estimation results of different GARCH models for Afghani exchange to US Dollar.

As we can see from the above table the log likelihood of GARCH (1, 1) model is lowest than the log likelihood of EGARCH (1,1) and GARCH-M (1,1) models. All the constant coefficients of variance Equations are significant at the conventional level of significance. And it is free from hetroscedasticity problem at the 5 % level of significance.

Conclusion and Recommendations

This paper examined three GARCH models namely GARCH, GARCH-M and EGARCH models for comparing their forecasting power for volatility of the return of Afghani exchange rate with US Dollar. All models are employed and their coefficients are interpreted. The results show that significant ARCH and GARCH effects are present in the data. That high volatility for some periods and for some period's low volatility. There is a period when volatility is high there is before a period when volatility is high and vice versa. It shows the time series of returns are conditionally heteroskedastic. There are some periods of high variance and some of low variance. There is volatility clustering. ADF unit root test result show data is stationary at level.

In GARCH (1,1) and GARCH-M (1,1) the coefficients of the GARCH (-1) is positive, significant and less than one, meaning that the effects last news on volatility is significant. The magnitude of the coefficient GARCH (-1) indicated the long memory of the variance. In GARCH-M for the mean equation, the coefficient of the risk premium is not significant. it showed no statistical evidence that the increased risk might cause an increase in returns. In EGARCH model the sign of C(5) is positive and significant indicates that a negative shock increases future volatility or uncertainty while a positive shock eases the effect on future uncertainty.

As we see from the Table 10. The log likelihood of GARCH (1, 1) model is lowest than the log likelihood of EGARCH (1,1) and GARCH-M (1,1) models. And it is free from hetroscedasticity problem at the 5 % level of significance.

Compare to the three models above, found the GARCH (1, 1) is the best model to explain the volatility of the return on the exchange of AFN with US Dollar. This is because all the constant coefficients and variables of variance equations are significant at the conventional level of significance at Table 10.

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