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Daily AFN/USD Exchange Rate Volatility Modeling and Forecasting Using ARCH/GARCH Family Models: Evidence from Afghanistan

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ABSTRACT

The main objective of this study is to give theoretical and empirical analysis of the volatility of Afghani (AFN) against United States Dollar (USD) exchange rate. Specifically, the study focuses on the behavior of exchange rate volatility using ARCH/GARCH family of models and shows that errors in the conditional mean equation have time-varying volatility. In addition, the current study aims to select the best model from four types of time series models (ARMA, ARCH, GARCH, EGARCH and TGARCH) to estimate and forecast AFN/USD exchange rate movements with the highest accuracy. This research uses data on the daily exchange rate of AFN/USD from Da Afghanistan Bank. The dependent variable is the AFN/USD exchange rate return, while its conditional volatility is modelled using an ARMA framework combined with ARCH, GARCH, EGARCH, and TGARCH models, in which volatility is explained by past innovations (ARCH effects) and past conditional variances (GARCH effects). The empirical results indicate that the GARCH (1,1) model provides the best overall performance in modeling and forecasting AFN/USD exchange rate volatility. The estimated GARCH parameter is highly significant, indicating strong volatility persistence, whereas the asymmetric effects captured by the EGARCH and TGARCH models are not statistically significant during the sample period. These findings provide useful implications for policymakers, financial institutions, investors, and researchers involved in exchange rate risk management and forecasting.

KEYWORDS: AFN/USD, EGARCH, Exchange Rate Volatility, GARCH, Time Series Analysis.

1. INTRODUCTION

The exchange rates are essential in the current era of globalization and financial liberalization for a small and open economy like Afghanistan for international trade and financial transactions (Krugman et al., 2018; Mishkin & Kiley, 2025). Exchange rate fluctuations impact the profits of trading companies, importers, exporters and financial institutions, contributing to a rise in exchange rate risk and uncertainty (Madura, 2021).

A fixed exchange rate can help investors, financial institutions, and policymakers make better investment, financing, and risk-management choices because it eliminates uncertainty and allows them to better project

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future costs and returns (Mishkin & Kiley, 2025). Therefore, exchange rate stability helps to mitigate risks associated with operations and finances.

The volatility of exchange rates can have important consequences on important macroeconomic variables such as profitability, prices, wages, jobs and economic activity (Obstfeld, 1998). Thus, the characteristics and dynamics of exchange rate changes are of great significance for economic policymakers and planners.

In recent years, financial econometrics have gained momentum, and there is a growing demand for quantitative models that can explain investors' behavior on the basis of expected returns and risk, as well as on the basis of volatility dynamics (Tsay, 2014; Brooks, 2019). Volatility is a crucial part of financial risk and investors and policymakers need suitable analytical tools to quantify, model and control the uncertainty in financial markets.

In the presence of time-varying variance, exchange rate volatility and unexpected economic shocks, time-series econometric models have been used to study exchange rate dynamics and the volatility behavior of exchange rates (Engle, 1982; Bollerslev, 1986). The most popular models for modeling conditional heteroskedasticity are the Autoregressive Conditional Heteroskedasticity (ARCH) and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. These models were first developed by Engle and later extended by Bollerslev, Baillie, Nelson and others and are now commonly used for volatility analysis of financial time series (Engle, 1982; Bollerslev, 1986; Nelson, 1991).

Fat tails and volatility clustering are two stylized facts generally found in financial time series data. These properties have been well captured and described by the GARCH family of models (Mandelbrot, 1963; Fama, 1965).

There is a large empirical literature that examines the volatility of exchange rates in various countries, using a range of econometric methods. The conclusions of these studies suggest that overall, ARCH/GARCH family models offer a viable tool for the volatility modelling and forecasting of exchange rates (Baillie & Bollerslev, 2002; Musa & Bello, 2014).

Therefore, the use of ARCH and GARCH family models for analyzing the exchange rate between the AFN and USD is appropriate and useful because the exchange rate of the two currencies, AFN/USD, can be affected by uncertainty, volatility, and also by changes in the exchange rate in the future (Engle, 1982; Bollerslev, 1986).

Afghanistan is a developing economy, and movements in the exchange rate have significant effects on trade, investment, and overall economic stability (Arian, 2025). Foreign exchange markets, imports, foreign currencies, and cash transactions are still the main means of payment for the country's financial system. Thus, changes in the AFN/USD currency rate have a direct impact on the economy.

Several factors affect the value of the Afghani against the U.S. dollar, including imports, exports, foreign aid inflows, demand for foreign currency, political conditions, and the monetary policy operations of Da

Afghanistan Bank (Arian, 2025). The impact of the exchange rate on production, price, money supply and the purchasing power of the household.

Therefore, analyzing exchange rate movements and volatility is vital for policymakers, traders, investors, and financial institutions to assess risks and improve exchange rate forecasting (Musa & Bello, 2014).

The effects of volatility of the AFN/USD exchange rate have been analyzed in this study using the ARCH, GARCH, EGARCH and TGARCH models. The goal is to find the best model for capturing exchange rate volatility and to gain insights that can aid effective economic policy decisions and exchange rate predictions.

Although many studies have been conducted on the level of volatility in exchange rates of developed and emerging markets, there is a lack of empirical evidence on the volatile dynamics of the AFN/USD exchange rate (Arian, 2025). This study aims to investigate the volatility of the Afghani against the USD during the last period, and offers a comparative analysis of ARCH, GARCH, EGARCH and TGARCH models based on the daily exchange rate data of Afghanistan. The results provide interesting information in an under-researched foreign exchange market regarding volatility persistence, asymmetric effects and prediction accuracy.

1.1 Research Problem

Volatile exchange rates place pressures on foreign trade, investment, financial planning and economic policy, especially in emerging markets where exchange rates can be highly volatile, persistent, and react in an asymmetric manner to shocks (Tiwary et al., 2022). These attributes demand econometric models that are able to account for time-varying volatility. The exchange rate between the AFN and USD plays a significant role in international trade and financial transactions in Afghanistan, but there is little empirical research on the daily volatility of AFN/USD and the prediction of the exchange rate by ARCH/GARCH-family models. Unlike ARCH and GARCH, both EGARCH and TGARCH can analyze the asymmetric impact of exchange rate shocks (Mohsin et al., 2019) and volatility clustering and persistence (Arian, 2025). Hence, this study aims to fill this gap by studying daily exchange-rate volatility of AFN/USD and analyzing different models, such as ARCH, GARCH, EGARCH and TGARCH, that can be used to estimate and forecast the volatility in Afghanistan.

1.2 Research Questions

1. Is there volatility clustering and time-varying volatility in the daily AFN/USD exchange rate?

2. Does the ARCH effect matter in the return of the exchange rate of AFN/USD?

3. Is the volatility of the exchange rate of AFN/USD persistent over time?

4. Is there any evidence that positive and negative shocks affect AFN/USD volatility asymmetrically?

5. What is the best ARCH/GARCH family model to model and forecast the volatility of AFN/USD?

1.3 Research Objectives

1.3.1 General Objective

To model and forecast the exchange rate volatility in AFN/USD for daily time periods with models from the ARCH/GARCH family and to determine which model is best performing.

1.3.2 Specific Objectives

1. To investigate the volatilities, feature of daily returns on the exchange rate of the pair AFN/USD.

2. To test for ARCH effects and volatility clustering.

3. To assess the persistence of AFN/USD exchange rate volatility.

4. To analyze the impact of positive and negative shocks on the economy in a non-symmetric way.

5. To see how to estimate and compare the ARCH, GARCH, EGARCH, and TGARCH models and determine which will best predict volatility of the AFN/USD.

1.4 Research Hypotheses

HI: The exchange rate returns of AFN/USD show a large ARCH effect.

H2: It is much more persistent in time that the exchange rate volatility of AFN/USD.

H3: The effects of positive and negative shocks on the volatility of the exchange rate of the AFN/USD are asymmetric.

H4: There is significant difference in the forecasting performance of the ARCH, GARCH, EGARCH and TGARCH models.

H5: The GARCH (1,1) model is the best model to model and forecast the volatility of the exchange rate in AFN/USD.

1.5 significance of the study

This study is important because it provides empirical evidence for modeling and forecasting the volatility of the exchange-rate of AFN/USD in Afghanistan with little empirical work done yet. The findings can aid policy makers and financial authorities to better comprehend the exchange-rate volatility and make better foreign-exchange and monetary-policy decisions.

The study can also benefit banks, businesses, importers, exporters, and investors, as it can offer information that can be used in foreign-exchange risk assessment, financial planning, and decision-making. Besides, the comparison of ARCH, GARCH, EGARCH and TGARCH models adds to the body of knowledge by selecting the appropriate model to forecast volatility of AFN/USD. Last but not least, the results can provide a reference for future researchers who are interested in exchange-rate volatility, financial econometrics, and foreign-exchange risk management in Afghanistan.

2. LITERATURE REVIEW

While a large number of econometric models have been used to study exchange rate dynamics in various countries, relatively few studies have focused on the volatility and forecasting ability of the AFN/USD exchange rate. There are different techniques used to model and predict exchange rates, such as Moving Average (MA), Autoregressive (AR), Exponential Smoothing, Autoregressive Integrated Moving Average (ARIMA) and Vector Autoregressive (VAR). These methods have different philosophies about how the exchange rate will behave and how predictable the movement will be.

In the literature, the most popular models for measuring and analyzing the volatility of exchange rates are the Autoregressive Conditional Heteroskedasticity (ARCH) model and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. Extended the model by (Bollerslev 1986) who developed the GARCH model, which permits past conditional variances to affect current volatility. There were later several extensions of the GARCH family that aimed at modelling more complex volatility dynamics. Notably (Nelson 1991); developed the Exponential GARCH (EGARCH) model, and (Glosten et al., 1993) and (Zakoïan, 1994) extended the GARCH framework to include thresholds that allow for modelling asymmetric reaction to market shocks.

Very early research on volatility modeling can be attributed to (Mandelbrot 1963) and (Fama 1965) who have observed the following stylized facts of financial time-series data: conditional heteroskedasticity, excess kurtosis (leptokurtosis), and volatility clustering. The stylized facts suggest that the volatility is not necessarily constant in time and support the use of ARCH/GARCH models in financial and exchange rate analysis.

There is a wealth of empirical evidence showing that GARCH-type models are successful in modelling exchange rate volatility. In addition to this, Benavides (2006) examined the volatility of the Mexican peso–U.S. dollar exchange rate and validated the usefulness of GARCH models in predicting the volatility of exchange rates. Likewise, Alam and Rahman, (2012) studied the volatility of the exchange rate within a certain time frame and showed that the volatility has been time varying. (Musa & Bello, 2014) used the GARCH family models to predict volatility of the Nigerian naira against the U.S. dollar and concluded that the GARCH family models were good predictors of the volatility of the Nigerian naira.

Further, (Ng & McAleer, 2004) used GARCH (1,1) and TARCH (1,1) models to analyse and forecast the volatility of the stock indices of S&P 500 and Nikkei 225 on a daily basis. They found that the TARCH (1,1) model was more suitable for the S&P 500 index while the GARCH (1,1) model was more suitable for the Nikkei 225 index. The findings in this paper are important in identifying the need for choosing the right volatility model for the type of financial series being studied.

More recently, Arian (2025) analyzed the dynamics and volatility of the AFN/USD exchange rate based on the daily exchange rate data for a selected sample period. The study used an ARMA–GARCH framework for modelling the conditional variance and the conditional mean of exchange rate returns. The empirical results indicated the existence of volatility clustering and strong volatility persistence, thus supporting the existence of conditional heteroskedasticity in the series of exchange rates AFN/USD. Moreover, study findings indicated that the GARCH (1,1) model outperforms the other models in the GARCH family, and that it offers the most accurate model for the exchange rate's volatility. The results provide valuable empirical evidence on volatility modeling, exchange rate risk management and economic policy analysis in Afghanistan.

Nevertheless, empirical studies on the volatility behavior of the AFN/USD exchange rate are still very limited. Hence, there is a need to further investigate the model, especially those of the ARCH/GARCH class that are able to account for the asymmetric volatility effect. In this context, the present study investigates the performance of the four models (ARCH, GARCH, EGARCH, and TGARCH) in modelling and forecasting exchange rate volatility by applying these models on daily AFN/USD exchange rate data to determine the most suitable model for modelling and forecasting the volatility of AFN/USD exchange rate in the context of Afghan foreign exchange market.

3. METHODOLOGY

3.1 Data and Econometric Methodology

This study adopts a quantitative empirical research methodology based on time-series econometric analysis. The study employs daily AFN/USD exchange rate data to examine the volatility dynamics of the exchange rate and to compare the performance of ARCH-family models in modelling and forecasting exchange rate volatility.

The analysis is conducted using the ARMA, ARCH, GARCH, EGARCH, and TGARCH models, and the forecasting performance of the estimated models is evaluated using standard forecast accuracy measures.

This study uses data on the daily exchange rate of Afghani/United States Dollar (AFN/USD) for analysis and volatility modelling. The statistical data is collected from Da Afghanistan Bank's registers. The study period for the sample is January 2025 to December 2025 so as to include the latest trends in the movements of the exchange rate of Afghani and the most recent volatility behavior of the Afghani exchange rate.

Furthermore, out-of-sample forecasting performance evaluation of the estimated models is conducted using the data for the first two months of 2026, to evaluate the accuracy and robustness of the models in predicting the future.

In this study, a number of econometric time-series models are used to model the time-series of the exchange rate, such as Autoregressive Moving Average (ARMA), Autoregressive Conditional Heteroskedasticity (ARCH), Generalized ARCH (GARCH), Exponential GARCH (EGARCH), and Threshold GARCH (TGARCH) models. Each of the following subsections briefly explains each model.

3.2 Autoregressive Moving Average Model (ARMA (p, q))

The ARMA (p, q) process is a process with an autoregressive (AR) component of order p and a moving average (MA) component of order q, where p and q are integers. The model can be written in the standard econometric form as shown below:

$$y_t = \mu + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots + \Phi_p y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q} \quad (1)$$

In which μ is the intercept parameter for the mean of y_t, and the error terms ε_t are assumed to be uncorrelated random variables with the following properties:

$$E[\varepsilon_t] = 0 \;\; Var[\varepsilon_t] = \sigma_t^2$$

If the process is stationary, then the mean of y_t remains constant across all time periods and is equal to ε_t, ensuring stability of the stochastic process over time.

3.3 Autoregressive Conditional Heteroskedasticity (ARCH) Model

The Autoregressive Conditional Heteroskedasticity (ARCH) model represents the first formal approach for modeling time-varying conditional variance. In econometrics, a model with conditional heteroskedasticity assumes that the variance of the innovation (error term) depends on past squared error terms. In most financial time series, volatility is therefore modeled as a function of lagged squared innovations.

The ARCH framework was introduced by Engle (1982), and the ARCH(q) specification is widely used to capture volatility in financial data.

Let ε_t denote the error term (innovation) from the mean equation of the return series. It is defined as:

$$\varepsilon_t = \sigma_t Z_t \text{ and } Z_t \sim N(0,1)$$

The conditional variance in an ARCH(q) model is specified as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \quad (2)$$

where: $\alpha_0 > 0$ and $\alpha_i \geq 0, i > 0$

These restrictions ensure that the conditional variance remains positive over time.

3.4 Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model

Volatility forecasting is not a straightforward task in financial time series analysis. However, a class of models known as the GARCH family has been widely successful in capturing and forecasting volatility dynamics in many empirical applications.

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is an extension of the ARCH framework that allows the conditional variance to depend not only on past squared errors but also on its own past values. This additional structure enables the model to capture persistent volatility more efficiently.

The general GARCH (p, q) model can be expressed as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \ldots + \beta_p \sigma_{t-p}^2 \quad (3)$$

where (p) represents the order of the GARCH terms (lagged conditional variances), and (q) represents the order of the ARCH terms (lagged squared residuals).

In this specification, the model captures volatility clustering and persistence in financial time series data more effectively than the standard ARCH model.

3.5 Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) Model

The Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model is a well-known extension of the GARCH framework introduced by Nelson (1991). Unlike the standard GARCH model, EGARCH does not impose non-negativity restrictions on the parameters, as it models the logarithm of the conditional variance. This specification ensures that the conditional variance remains strictly positive, even when the estimated parameters take negative values.

A key advantage of the EGARCH model is its ability to capture asymmetric effects, commonly known as the leverage effect. This implies that negative and positive shocks of the same magnitude may have different impacts on volatility, a feature that standard GARCH models cannot adequately capture.

The EGARCH (1,1) model can be expressed as:

$$\ln h_t^2 = \alpha_0 + \alpha_1 \left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| + \phi \frac{\varepsilon_{t-1}}{h_{t-1}} + \beta_1 \ln h_{t-1}^2 \quad (4)$$

where ϕ (phi) represents the leverage parameter, which measures the asymmetric effect of shocks on conditional volatility. In this specification, a negative value of ϕ (phi) indicates that negative shocks increase volatility more than positive shocks of the same magnitude.

3.6 Threshold Generalized Autoregressive Conditional Heteroskedasticity (TGARCH) Model

It is a modified version of the GARCH model, which incorporates asymmetric effects in the behavior of the volatility process, known as the Threshold Generalized Autoregressive Conditional Heteroskedasticity (TGARCH) model. In particular, it provides a way for positive and negative shocks to affect conditional volatility differently. Negative shocks are more likely than positive shocks of the same magnitude to have a larger effect on volatility in financial markets and exchange rate dynamics.

The TGARCH model is also referred to as the GJR-GARCH model, as it was introduced by Glosten, Jagannathan, and Runkle (1993).

The TGARCH (1,1) model is specified as follows:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma d_{t-1}\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (5)$$

where (d_{t-1}) is a dummy variable defined as:

$$d_{t-1} = \begin{cases} 1, & \text{if } \varepsilon_{t-1} < 0 \\ 0, & \text{if } \varepsilon_{t-1} \geq 0 \end{cases}$$

This means that if the shock is negative, then $d = 1$, and if the shock is positive, then $d = 0$.

3.7 Forecast Evaluation Criteria

Commonly used measures for evaluating and comparing the forecasting performance of econometric models include the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Theil's Inequality Coefficient. In this study, the selected models are evaluated based on these forecasting accuracy criteria.

The error statistics are defined as follows:

$$MAE = \frac{\sum_{t=1}^{T+h} |\hat{y}_t - y_t|}{h} \qquad RMSE = \sqrt{\frac{\sum_{t=1}^{T+h} (\hat{y}_t - y_t)^2}{h}}$$

These two measures depend on the scale of the dependent variable. Therefore, they are considered scale-dependent measures and are commonly used for comparing competing models over the same dataset. A lower value of MAE or RMSE indicates better forecasting performance.

The remaining measures are scale-independent. The Mean Absolute Percentage Error (MAPE) and The Theil's Inequality Coefficient are defined as:

$$MAPE = 100 \times \left[\frac{\sum_{t=1}^{T+h} \left|\frac{\hat{y}_t - y_t}{y_t}\right|}{h}\right] \quad Theil\ Inequality\ Coefficient = \frac{\sqrt{\frac{\sum_{t=1}^{T+h} (\hat{y}_t - y_t)^2}{h}}}{\sqrt{\frac{\sum_{t=1}^{T+h} \hat{y}_t^2}{h}} + \sqrt{\frac{\sum_{t=1}^{T+h} y_t^2}{h}}}.$$

The value of Theil's U lies between 0 and 1, where a value closer to zero indicates a perfect fit and superior forecasting accuracy.

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4. RESULTS AND DISCUSSION

4.1 Descriptive Statistical Properties

To examine the distributional properties of the exchange rate returns, several descriptive statistical measures are reported in Table 1.

Table 1: Summary Statistics

Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob.
68.479	2.054	0.989	3.936	32.736	<0.001

Table 1: *reports descriptive statistics for the AFN/USD exchange rate level series, whereas all ARCH-family models are estimated using the corresponding return series.*

As expected in exchange rate time series data, the Afghani exchange rate against the US Dollar fluctuated between 63 and 77.75 during the sample period, with an average value of approximately 68.48, indicating noticeable market variability.

The relatively high standard deviation suggests substantial volatility in the exchange rate series. The positive skewness value (0.989) indicates that the distribution is right-skewed, implying a higher probability of upward movements in the exchange rate and evidence of asymmetric behavior.

The kurtosis value exceeds 3, indicating a leptokurtic distribution, which suggests the presence of fat tails and a higher likelihood of extreme observations compared to the normal distribution.

Finally, the Jarque-Bera test results and the associated p-value (< 0.001) confirm that the exchange rate series is not normally distributed. Therefore, the null hypothesis of normality is strongly rejected.

4.2 Stationarity Tests

Time-series models like ARMA, ARCH, GARCH, EGARCH, and TGARCH should be estimated after first checking for stationarity of the data. The stationarity properties of the exchange rate series are examined as a preliminary step for these models, since they are used in the present study.

The concept of stationarity is critical in time-series analysis because non-stationary time-series can yield incorrect results and make poor statistical inferences. There are three widely used methods: graphical, correlogram and unit root testing.

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Figure 1: Graphical Analysis

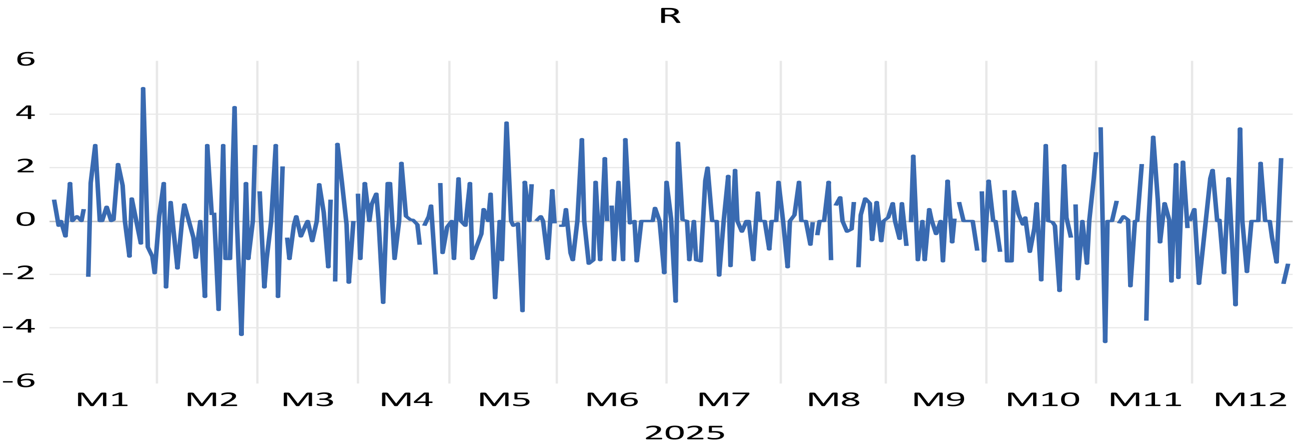
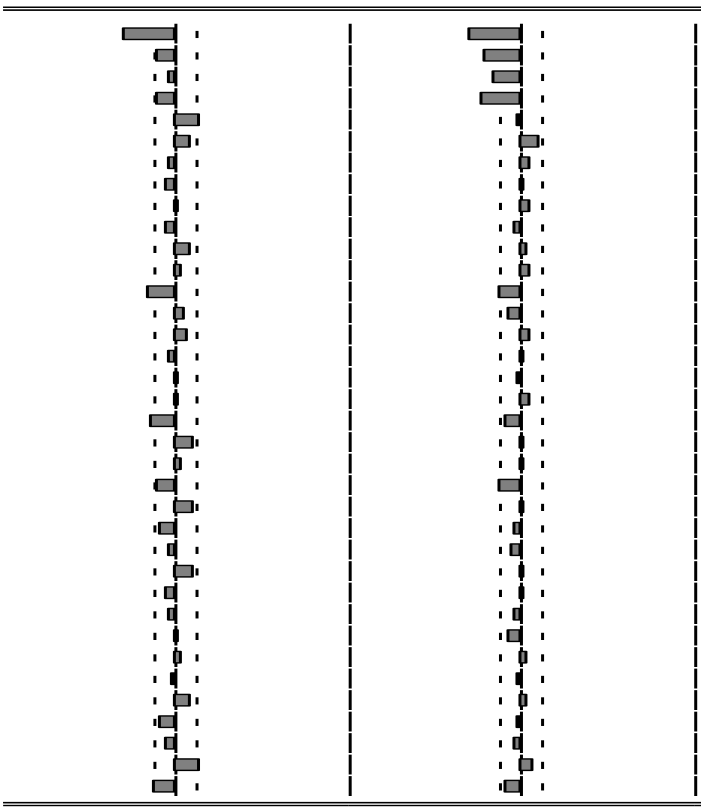


Figure 2: Correlogram



Date: 06/13/26 Time: 21:45
Sample (adjusted): 1/04/2025 12/30/2025
Included observations: 303 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.304	-0.304	28.239	0.000
		2	-0.114	-0.227	32.215	0.000
		3	-0.026	-0.160	32.423	0.000
		4	-0.110	-0.240	36.164	0.000
		5	0.145	-0.020	42.670	0.000
		6	0.094	0.100	45.437	0.000
		7	-0.047	0.058	46.135	0.000
		8	-0.055	-0.002	47.097	0.000
		9	0.016	0.050	47.179	0.000
		10	-0.055	-0.040	48.118	0.000
		11	0.097	0.040	51.107	0.000
		12	0.029	0.051	51.380	0.000
		13	-0.169	-0.136	60.444	0.000
		14	0.046	-0.067	61.118	0.000
		15	0.081	0.058	63.212	0.000
		16	-0.027	0.006	63.448	0.000
		17	0.018	-0.011	63.552	0.000
		18	0.008	0.064	63.575	0.000
		19	-0.153	-0.095	71.177	0.000
		20	0.109	0.001	75.082	0.000
		21	0.035	0.022	75.486	0.000
		22	-0.111	-0.115	79.518	0.000
		23	0.110	0.005	83.489	0.000
		24	-0.096	-0.038	86.556	0.000
		25	-0.029	-0.058	86.828	0.000
		26	0.114	0.019	91.177	0.000
		27	-0.057	-0.007	92.270	0.000
		28	-0.042	-0.040	92.860	0.000
		29	-0.003	-0.066	92.863	0.000
		30	0.037	0.039	93.317	0.000
		31	-0.014	-0.013	93.385	0.000
		32	0.083	0.031	95.734	0.000
		33	-0.092	-0.009	98.622	0.000
		34	-0.050	-0.044	99.493	0.000
		35	0.131	0.068	105.45	0.000
		36	-0.136	-0.083	111.83	0.000

The autocorrelation coefficients from the correlogram suggest that the coefficients are quickly approaching zero, and do not show the slow decay characteristic of a unit-root process. A few autocorrelation coefficients are statistically different from zero, and the Ljung–Box Q-statistics do not support the null hypothesis of no

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serial correlations, but the overall structure of the autocorrelation suggests that the series is stationary. If there is significant short-run dependence, the series is not white noise and an ARMA specification might be adequate for modeling the series before estimating the volatility.

Table 2: Unit Root Test Results for the Exchange Rate Return Series

H_0: Exchange rate has a unit root

Test	ADF			PP		
	Test Statistic	Critical value	P-value	Test Statistic	Critical value	P-value
Intercept	-3.389562	-2.880088	0.0128	-30.57403	-2.879267	0.0001
Intercept & Trend	-3.702037	-3.439075	0.0251	-4.562909	-3.437629	0.0016

Both of the Augmented Dickey–Fuller and Phillips–Perron tests support the hypothesis that the series of the exchange rate return is stationary under two alternative models: intercept and intercept with trend. The p-values are all less than 5% and the test statistics are all less than their critical values. Thus, we can reject the null hypothesis of a unit root.

These results reinforce the result obtained above that there is no unit root in the exchange rate return series and that the exchange rate return series is stationary in level. The series is thus stationary for ARCH/GARCH family modelling such as ARCH, GARCH, EGARCH and TGARCH.

4.3 ARCH-LM Test

To determine whether the exchange rate return series exhibits conditional heteroskedasticity, the ARCH-LM test was performed on the residuals of the estimated ARMA (1,1) model. The test results are presented in Table 3.

Table 3: ARCH-LM Test Results

Statistic	**Value**	**P-value**
F-statistic	4.218	0.0419
Obs*R-squared	4.302	0.0380

The ARCH-LM test indicates the presence of ARCH effects in the residuals of the estimated ARMA model. Since the p-values of both the F-statistic (0.0419) and Obs*R-squared (0.0380) are below the 5% significance

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level, the null hypothesis of no ARCH effects is rejected. These findings confirm the existence of conditional heteroskedasticity and volatility clustering in the AFN/USD exchange rate returns, providing statistical justification for estimating the ARCH/GARCH family models.

4.4 Model Fitting

The distribution of the exchange rate level series is found to be non-normal as suggested by the descriptive statistics in Table 1. The excess kurtosis and the failure of the normality assumption indicate that there is volatility clustering, which is typically observed in financial time-series data. Hence, volatility modelling based on the ARCH/GARCH family of models can be used to model the dynamics of exchange rate returns.

According to the results of estimation in Table 3, ARCH effect is not statistically significant in the ARCH (1) model, because its p-value is greater than 0.05. The GARCH term in the GARCH (1,1) model, on the other hand, is very significant, suggesting that the exchange rate return series of AFN/USD has high volatility persistence.

Also, the asymmetry parameters of EGARCH (1,1,1) and TGARCH (1,1,1) are not statistically significant (p-value > 0.05). Such a result implies that there is little difference in the effect of positive shocks and negative shocks on exchange rate volatility over the sample period.

For comparing the competing models, the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) were used. According to the estimated specifications, the GARCH (1,1) model is the best model to estimate the volatility dynamics of the exchange rate returns of the AFN/USD currency.

Table 4: Comparison of the Estimated ARCH-Family Models

Models	**Coefficients and (Prob.)**				**AIC**	**SIC**
	Constant	**ARCH Effect**	**Asymmetry Effect**	**GARCH (-1) Effect**		
ARCH (1)	1.905295 (0.0000)*	-0.044836 (0.6803)			3.497178	3.592475
GARCH (1,1)	0.227729 (0.3268)	0.038160 (0.5337)		0.840241 (0.0000)*	3.489122	3.603478

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EGARCH (1,1,1)	0.020312 (0.8629)	0.110452 (0.4609)	0.015770- (0.7857)	0.826325 (0.0000)*	3.497138	3.630552
TARCH (1,1,1)	0.242016 (0.3592)	0.023830 (0.7160)	0.030076 (0.6745)	0.831499 (0.0000)*	3.500467	3.633881

Note: *The Prob. values are enclosed in bracket and * marked indicate that the estimated coefficients are significance at the 5% level of significance*

The model with the lowest Theil's Inequality Coefficient (TI) is that of ARMA (1,1)-GARCH (1,1) with value of 0.459977, which is better than other models. Furthermore, the smallest mean absolute error (MAE) value is obtained using this model, having a value of 0.843271, which indicates that the model has a smaller average error in forecasting.

The ARMA (1,1)-ARCH (1) model gives the lowest value of Root Mean Square Error (RMSE) 1.082129, but the ARMA (1,1)-GARCH (1,1) model shows to be the best model in terms of MAE and Theil's Inequality Coefficient.

The ARMA (1,1)-EGARCH (1,1,1) model has relatively moderate forecasting accuracy, while the ARMA (1,1)-TGARCH (1,1,1) model has relatively poor forecasting accuracy, as evidenced by the highest RMSE, MAE and TI values compared with other estimated models.

In general, the ARMA (1,1)-GARCH (1,1) model is recognized as the most suitable and accurate model for forecasting exchange rate returns volatility of AFN/USD during the study period, based on the results of comparative analysis of RMSE, MAE, and Theil's Inequality Coefficient measures.

Table 5: Comparison of Forecasting Accuracy Across the Estimated Models

Models	RMSE	MAE	TI
ARMA (1,1) - ARCH (1)	1.082129	0.891352	0.465410
ARMA (1,1) -GARCH (1,1)	1.205484	0.843271	0.459977
ARMA (1,1)-EGARCH (1,1,1)	1.116900	0.862194	0,500230
ARMA (1,1) – TARCH (1,1,1)	1.430647	0.957353	0.963258

Note: *MAPE was not included in the forecast evaluation as the exchange rate return series has zero or near zero values that may cause unstable and misleading percentage error measures. In this regard, the performance of the forecasts was measured by RMSE, MAE and Theil's Inequality Coefficient (TIC), all of which are more appropriate for volatility forecasting applications.*

4. 5 DISCUSSION

The results of this study have empirical significance on the behavior, persistence and forecasting of exchange rate volatility in USD/AFD in Afghanistan on daily time frames. The results show that the exchange-rate series is volatile and has volatility clustering, i.e., short periods of high volatility are followed by further periods of high volatility, and short periods of low volatility are followed by further periods of low volatility. This behavior is consistent with the well-established properties of financial time-series data and lends credence to the hypothesis that one should consider using conditional volatility models as opposed to the traditional models which assume a constant variance. Volatility clustering also fits in with the original GARCH framework (Bollerslev, 1986) and earlier evidence in the exchange rate markets of developing countries (Katusiime et al., 2016).

This is a significant finding of the study because it suggests that shocks to the exchange rate of AFN/USD have longer-term impact than was previously thought. An unanticipated exchange rate movement can, in effect, bring uncertainty not only on the day of the shock, but also when trading later in the day. Afghanistan's ability to appreciate or depreciate its currency has a significant impact on the following factors: cost of imports, foreign-currency transactions, business planning and financial risk management. Given that volatility is continuing, there is a need to pay close attention to exchange rate shocks by both the policymakers and the market participants.

The results also reveal that the GARCH (1,1) model has the best overall performance from the models under consideration. This suggests that the conditional volatility as well as recent innovations in the exchange rate are significant for current AFN/USD volatility. The good performance of the GARCH (1,1) model could be due to its simplicity and flexibility, which enables it to account for both volatility clustering and persistence without adding any model complexity. The same study results have been reported by previous exchange-rate studies, where GARCH-type models have been found to have high power in modelling the persistence of the conditional variance (Katusiime et al., 2016).

An important implication of the superiority of the GARCH (1,1) model is related to forecasting. More complex models like EGARCH and TGARCH can be used to model asymmetric responses, but more complex doesn't necessarily mean better forecasting. As pointed out in previous research, the model that is statistically best fit may not be necessarily the most accurate forecast model and hence direct comparison of competing volatility models is of importance (Lee, 2009). The results of the present study indicate that the standard GARCH specification is adequate to explain the major volatility features of the AFN/USD exchange rate for the sample period.

The EGARCH and TGARCH models present no evidence of the statistical significance of asymmetry effects, however. This finding implies that positive and negative exchange rate shocks of equal magnitude do not seem to have significantly different effects on the subsequent volatility of AFN/USD. In other words, there is no evidence to confirm that a strong leverage-type or asymmetric volatility effect exists in the AFN/USD market during the study period. The result is in contrast with some earlier studies on exchange rates of developing countries which have detected marked asymmetric reactions to exchange-rate shocks (Bollerslev, 1986).

These disparities could be due to the differences in the market structure, monetary policy, exchange-rate policy, sample periods or the characteristics of the economic shocks in the respective countries.

If there are no important asymmetric effects, this does not imply that exchange-rate shocks are unimportant. Instead, it suggests that the impact of the shock per se does not seem to be a significant factor in determining future market volatility in AFN/USD. The size and duration of past shocks and conditional variance seems to be more important. As the strong performance and high persistence parameter of the GARCH (1,1) model, this interpretation also holds true.

In general, the results indicate that the volatility of the AFN/USD exchange rate market is first and foremost clustered (volatility clustering) and persistent (persistent market). The results would be helpful to the policy makers, financial institutions, importers, exporters, investors, and other market players. It is particularly noteworthy that GARCH (1,1) forecasts seem to do well, suggesting that past volatility and recent shocks to the exchange rate may be useful for predicting exchange-rate risk. In conclusion, the model will be useful as an analytical tool to track currency risks and for financial and economic decisions in Afghanistan.

Academically, this study is a valuable addition to the limited empirical literature available on the foreign exchange market in Afghanistan in that it is supported with empirical data from the daily exchange rates of AFN/USD. A comparison of ARCH, GARCH, EGARCH and TGARCH models will show that the choice of a model should be made on the basis of empirical performance and not on the basis of theory alone. The results also serve as a framework for future research to determine if the volatility of the AFN/USD exchange rate varies in time, especially during major economic, monetary, and/or foreign-exchange market shocks.

5. CONCLUSION

The GARCH (1,1) model is determined to be the most suitable model for volatility analysis and prediction of exchange rate returns for the AFN/USD market by using the combined analysis of the results presented in Tables 4 and 5. The model has the smallest Akaike Information Criterion (AIC), which suggests it is the best fit model of the competing models. Moreover, the GARCH parameter is statistically significant and is evidence that the series of exchange rate returns is persistent in terms of volatility.

The other results for the forecast evaluation support the superiority of the GARCH (1,1) model. The model has the lowest Mean Absolute Error (MAE) and Theil's Inequality Coefficient (TI) as reported in Table 4, which also shows the performance of the other models. The ARCH (1) specification has a lower Root Mean Square Error (RMSE), but the overall evaluation using a variety of forecast accuracy indicators shows a preference for the GARCH (1,1) specification.

Hence, it is concluded that the most appropriate model to model and forecast the volatility of the daily returns of AFN/USD exchange rate during the study period is the GARCH (1,1) model. The findings also corroborate the existence of a persistent volatility in the foreign exchange market of AFN/USD and indicate the significance of exchange rate volatility analysis using GARCH type models in Afghanistan.

The result of this study can be beneficial for the policy makers, financial institutions, foreign exchange dealers and investors who want to know and control the exchange rate risk in Afghanistan. The analysis can be extended in the future by using longer sample periods, data at a higher frequency, and/or alternative volatility models to explore further the dynamics of AFN/USD exchange rate.

5.1 Recommendations

Based on the findings of this study, it is recommended that policymakers regularly monitor exchange rate volatility using appropriate econometric models, such as GARCH, to support timely policy decisions. Financial institutions, investors, and foreign exchange market participants should incorporate volatility forecasting into their risk management and investment strategies. Researchers and practitioners are also encouraged to apply volatility models when evaluating exchange rate behavior in Afghanistan to improve forecasting accuracy and decision-making.

5.2 Limitations

Despite its contributions, this study has several limitations. First, the analysis is based on a relatively short sample period covering daily AFN/USD exchange rate data from January 2025 to December 2025. A longer sample could provide more robust evidence on the persistence and structural changes in exchange rate volatility. Second, the study considers only the bilateral AFN/USD exchange rate and does not include other important foreign currencies. Third, the analysis focuses exclusively on univariate ARCH-family models without incorporating macroeconomic variables such as inflation, interest rates, foreign reserves, monetary policy interventions, political events, or external economic shocks that may influence exchange rate volatility. Finally, the forecasting performance was evaluated using a limited number of forecast accuracy measures.

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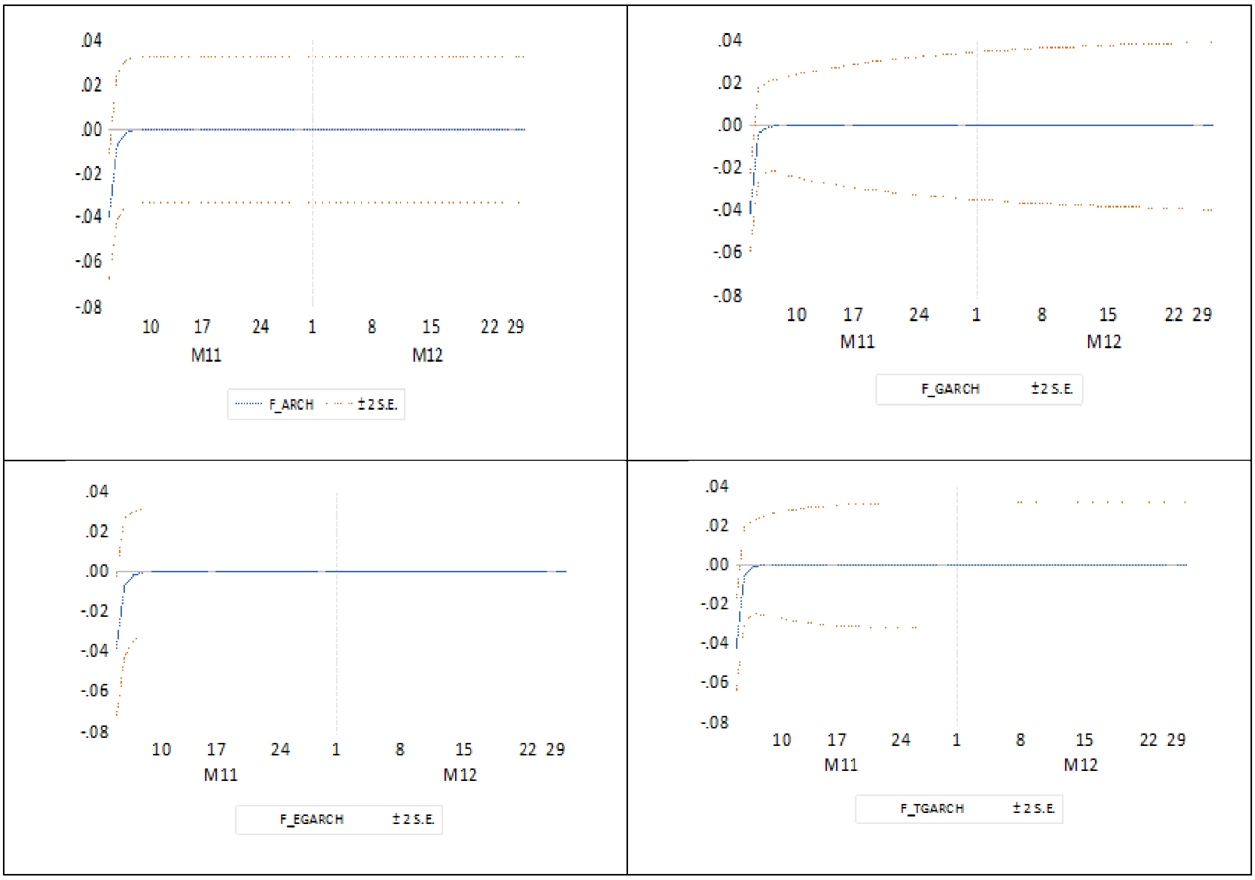
5.3 Future Research Directions

Future studies may extend this research in several ways. Researchers may employ longer and higher-frequency datasets to improve the robustness of volatility estimates. Future work may also compare the performance of alternative volatility models, including APARCH, IGARCH, FIGARCH, Component GARCH, Markov-Switching GARCH, and stochastic volatility models. Moreover, incorporating macroeconomic and political variables into multivariate volatility frameworks may provide deeper insights into the determinants of exchange rate volatility in Afghanistan. Finally, comparative studies involving exchange rates with other major currencies and machine learning-based forecasting approaches could further enhance the understanding and prediction of exchange rate movements.

Figure 3: Forecasts of AFN/USD Exchange Rate Volatility Using Alternative ARCH-Family Models.



5.4 Conflict of Interest

Author express no conflict of interest in any part of the research.

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