Original Article *Journal of Multidisciplinary Research Advancements (JOMRA), Vol. 3, No. 2 (2025), 218 – 225*
e-ISSN 2990-7721 Available online at https://www.nepjol.info/index.php/jomra

Modeling and Forecasting NPR-USD Exchange Rate Volatility Using GARCH Family Models

Bidur Gautam[1*], Chandra Kant Sapkota[2], Bindu Gnawali[3]

[1]Assistant Professor, Uniglobe College, Kathmandu, Nepal
[2]Assistant Professor, Nepal Commerce Campus, Tribhuvan University, Kathmandu, Nepal
[3]Assistant Professor, Patan Multiple Campus, Tribhuvan University, Lalitpur, Nepal

**Corresponding author: gautambidur16@gmail.com*

Abstract: In terms of business, exchange rates are crucial factors influencing a nation's economic prosperity, impacting investors, government bodies, policymakers, and various other components. This research aimed to examine the dynamics of the Nepalese rupee relative to the US dollar in the Nepalese foreign exchange market, recognising that exchange rates play a crucial role in competitiveness. The primary goal of this study was to assess the applicability of GARCH-type models, including GARCH, TGARCH, and EGARCH, for modelling the NPR-USD exchange rate using daily time series data provided by Nepal Rastra Bank. The analysis compared the results with ARIMA models. The data analysed spans from January 1, 2014, to March 30, 2024, with in-sample and out-of-sample datasets covering January 1, 2014, to September 30, 2023, and October 1, 2023, to March 30, 2024, respectively. The study also involved exploratory data analysis of the variables, which underwent diagnostic tests, including unit root and normality tests. A key finding is that all GARCH-type models indicate that historical exchange rate volatility has a significant impact on current volatility. Three models were developed and tested for diagnostic accuracy, with the Threshold GARCH model demonstrating suitability and stability. The findings concluded that negative shocks have a greater effect on volatility than positive shocks. Furthermore, this methodology is recommended for future studies and can be applied for predicting exchange rate volatility in Nepal.

Keywords: *Arima, Egarch, Forecasting, Garch, Tgarch, Volatility*

Conflicts of interest: None
Supporting agencies: None

Received 20.08.2025 Revised 18.11.2025 Accepted 14.12.2025

Cite This Article: Gautam, B. (2025). Modeling and Forecasting NPR-USD Exchange Rate Volatility Using GARCH Family Models. *Journal of Multidisciplinary Research Advancements*, 3(2), 218-225.

1. Introduction

Exchange rate volatility is a significant concern for economies heavily reliant on international trade, particularly for developing nations like Nepal, where currency fluctuations have a direct impact on inflation, foreign investment, and macroeconomic stability (Paudel & Burke 2015). Nepal's economy, heavily dependent on imports and remittances (Phaju 2021), is vulnerable to external shocks, making the stability of the Nepalese rupee (NPR) against major currencies, such as the US dollar (USD), a priority for policymakers (Dahal & Raju 2022). The NPR-USD exchange rate has exhibited significant volatility, depreciating from NPR 68.725 per USD in 2000 to NPR 133.56 in 2024, raising concerns about exchange rate risk management (NRB, 2024). Understanding and forecasting this volatility is essential for businesses, investors, and the Nepal Rastra Bank (NRB) to formulate effective monetary and trade policies.

Despite the growing body of literature on exchange rate volatility, few studies have focused on Nepal's unique exchange rate regime, which pegs the NPR to the Indian rupee (INR) while floating against other currencies (Thapa 1996). Existing research on Nepal's exchange rate dynamics has primarily examined macroeconomic determinants (Dahal & Raju 2022) or the impact of exchange rate policies on trade (Paudel & Burke 2015), with limited attention to modeling volatility using advanced econometric techniques. While generalised autoregressive conditional heteroskedasticity (GARCH) models are widely employed in financial econometrics (Bollerslev 1986), their asymmetric variants, such as threshold GARCH (TGARCH) and exponential GARCH (EGARCH), remain underexplored in the

Nepalese context. These models are important for capturing leverage effects, where negative shocks (e.g., economic crises) exert a stronger impact on volatility than positive shocks of the same magnitude (Black 1976). Given Nepal's exposure to global economic uncertainties, such as commodity price shocks and geopolitical instability, a nuanced understanding of asymmetric volatility is vital for risk management.

This study addresses this gap by evaluating the performance of GARCH-family models, GARCH(1,1), TGARCH(1,1), and EGARCH(1,1), in modeling and forecasting the NPR-USD exchange rate volatility. Using daily exchange rate data from 2014 to 2024, we assess the models' ability to capture volatility clustering, persistence, and asymmetry. Our analysis builds on the work of Hansen and Lunde (2005), who demonstrated the superiority of GARCH-type models in forecasting financial volatility, but extends it to a pegged-exchange-rate context.

The TGARCH model's superior forecasting accuracy (lowest RMSE and MAE) suggests its utility for NRB in managing exchange rate risks. These results contribute to the broader literature on exchange rate volatility in small, trade-dependent economies and offer practical insights for policymakers aiming to stabilise the NPR amidst global financial uncertainties.

2. Relevant Literatures

2.1. Theoretical Foundations: ARCH/GARCH Models and Leverage Effects

The modeling of financial volatility has evolved significantly since Engle's (1982) introduction of the autoregressive conditional heteroskedasticity (ARCH) model, which captures time-varying volatility by linking current variance to past squared residuals. Bollerslev's (1986) generalized ARCH (GARCH) model extended this framework by incorporating lagged conditional variances, offering a more parsimonious way to model persistence in volatility. These models address a key limitation of traditional econometric approaches, which assume constant variance (homoskedasticity), an assumption often violated in financial time series (Brooks 2008).

A critical advancement in volatility modeling is the recognition of asymmetric effects, where negative shocks (e.g., economic crises) have a different impact on volatility than positive shocks of the same magnitude (BenSaida 2021). Black (1976) attributed this "leverage effect" to firms' financial structures, where asset value declines increase leverage, thereby amplifying volatility. Subsequent models, such as TGARCH (Glosten et al. 1993) and EGARCH (Nelson 1991), formalized this asymmetry. TGARCH introduces a dummy variable to differentiate between shock signs, while EGARCH employs logarithmic transformations to capture both magnitude and sign effects. These models are particularly relevant for exchange rates, where central bank interventions and market sentiment often create asymmetric responses (Antonakakis 2007).

2.2. Evidence on Exchange Rate Volatility

Empirical studies across various economies have shown the superiority of GARCH-family models in forecasting exchange rate volatility. Hansen and Lunde (2005) compared 330 volatility models and found that GARCH(1,1) was robust for daily exchange rate data. Similarly, Vilasuso (2002) demonstrated that fractionally integrated GARCH (FIGARCH) outperforms standard GARCH in capturing long memory in USD exchange rates. Asymmetric effects are well-documented. Epaphra (2017) demonstrated EGARCH's leverage effect in Tanzanian shilling volatility, while Dwarika et al. (2021)identified TGARCH as optimal for South Africa's rand, finding that adverse shocks increase volatility more than positive shocks.

Research on Nepal's exchange rate volatility remains limited and often overlooks asymmetric modeling. Thapa (1996) analysed NPR-USD trends, relying on linear models, whereas Dahal and Raju (2022) examined the macroeconomic determinants of Nepal's exchange rate without addressing volatility clustering. Paudel and Burke (2015) focused on the trade impacts of Nepal's peg to the INR but did not explore the dynamics of volatility. Notably, no study has systematically applied TGARCH or EGARCH to NPR-USD data, despite Nepal's vulnerability to external shocks (e.g., India's demonetization in 2016, COVID-19 disruptions).

While the existing literature provides a foundation for understanding Nepal's exchange rate environment, this study aims to address three critical gaps in the existing knowledge. First, a methodological gap exists, as previous studies on Nepal have predominantly relied on linear or symmetric volatility models (Thapa, 2002; Paudel & Burke, 2015), failing to account for the asymmetric impact of positive and negative shocks—a phenomenon well-documented in financial markets. Second, there is a contextual gap in the application of advanced volatility models within a pegged exchange rate regime, such as Nepal's, where the NPR-INR peg may create unique volatility dynamics not observed in free-floating currencies. Third, from a policy perspective, existing studies have not sufficiently connected volatility forecasting to the practical challenges of managing USD liquidity and exchange rate risk faced by the Nepal Rastra Bank.. This study contributes by addressing all three dimensions, offering a more robust, context-sensitive, and policy-relevant understanding of exchange rate volatility in Nepal.

3. Materials and methods

This study employs a robust econometric framework to model and forecast the volatility of the NPR-USD exchange rate. The methodology consists of four key stages: (1) data collection and transformation, (2) preliminary tests for stationarity and heteroskedasticity, (3) model specification and estimation using GARCH-family models, and (4) out-of-sample forecasting evaluation.

3.1. Data Collection and Transformation

The analysis uses daily NPR-USD exchange rates (selling price) from January 1, 2014, to March 30, 2024, sourced from the Nepal Rastra Bank (NRB) database. The raw exchange rate series$y_t$is transformed into logarithmic returns r_t to achieve stationarity and normalize variance, calculated as:

$r_t = ln\left(\frac{y_t}{y_{t-1}}\right)$ ....(1)

where r_t is the exchange rate return for any period t, y_t is the exchange rate at time t, and y_{t-1} is the exchange rate at time t-1. This transformation mitigates skewness and stabilizes variance, making the series suitable for volatility modeling (Tsay 2005).

3.2. Preliminary Tests

3.2.1. Stationarity Tests

To avoid spurious regression, the study checks stationarity using:

Augmented Dickey-Fuller (ADF) Test: Tests the null hypothesis of a unit root (non-stationarity) against the alternative of stationarity. The ADF equation includes a constant and lagged differences:

$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-1} + \mu_t$................... (2)

Phillips-Perron (PP) Test: A non-parametric alternative to ADF that accounts for serial correlation and heteroskedasticity in the error term.

Both tests confirm the return series is stationary (I(0)), while the level series (exchange rate) is integrated of order 1 (I(1)) (Dickey & Fuller, 1979).

3.2.2. Heteroskedasticity Tests

The presence of volatility clustering is verified using:

ARCH-LM Test: Regresses squared residuals on their lagged values to detect ARCH effects. The null hypothesis of no ARCH effects is rejected if the F-statistic or Obs*R-squared is significant (Engle 1982).

Ljung-Box Q-Test: Assesses autocorrelation in squared returns, further confirming volatility clustering (Ljung & Box 1978).

3.3. Model Specification

3.3.1. Mean Equation: ARIMA (2,1,2)

The ARIMA (2,1,2) model is selected for the conditional mean based on the lowest Akaike Information Criterion (AIC) and significant coefficients:

$(1 - \varphi_1 L - \varphi_2 L^2)(1 - L)Y_t = (1 + \theta_1 L + \theta_2 L^2)\varepsilon_t$ .... (3)

3.3.2. Volatility Models

GARCH (1,1): Models conditional variance as a function of past squared residuals and past variance:

$\sigma^2_t = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1}$ .... (4)

TGARCH (1,1): Captures asymmetry via a dummy variable.

$\sigma^2_t = \omega + \alpha\varepsilon^2_{t-1} + \gamma\varepsilon^2_{t-1}I_{t-1} + \beta\sigma^2_{t-1}$ .... (5)

A significant γ indicates negative shocks increase volatility more (Glosten et al. 1993).

EGARCH (1,1): Log-specification ensures positive variance and models leverage effects:

$\gamma<0$ implies negative shocks have a larger impact (Nelson 1991).

$\ln(\sigma^2_t) = \omega + \alpha|\varepsilon_{t-1}/\sigma_{t-1}| + \gamma(\varepsilon_{t-1}/\sigma_{t-1}) + \beta\ln(\sigma^2_{t-1})$ .... (6)

3.3.3. Model Selection Criteria
The best-fitting model is chosen based on:
Akaike Information Criterion (AIC) and Schwarz Criterion (SIC): Penalize model complexity.
Log-likelihood: Higher values indicate better fit.
Significant coefficients: t-statistics with $p<0.05$.
To calculate a relative value according to the AIC in the model, the maximum likelihood estimation, and the number of parameters independent variables are used. So,

$$AIC = 2p - 2\ln(L) \text{..........(7)}$$

where p denotes the number of independent variables employed and L denotes the likelihood value estimated at the parameter estimates. The value measures the model's goodness of fit, alongside imposing penalties for overfitting the data; therefore, a lower AIC score suggests a better goodness of fit and less overfitting. Similar to AIC but not likely, the Bayesian Information Criterion (BIC) considers the number of data observations and is shown as

$$BIC = \text{In}(n)p - 21n(L) \text{ ....(8)}$$

As n is the number of data points. Lowering the value of BIC shows smaller penalty terms, which is better. After the sufficiency of the models is discussed, model selection is applied to evaluate which empirical model is the best fit for modelling the variance.

3.4. Forecasting Evaluation

The dataset was split into in-sample Data from January 1, 2014, to September 30, 2023 (estimation) and out-of-sample Data from October 1, 2023, to March 30, 2024 (forecasting).
The model can provide a good fit to the y of samples used to estimate the parameters. In an out-of-sample comparison, the first part of the sample is used to estimate the model's parameters, and the latter part of the sample is reserved to evaluate the forecasting function.
Assume that the study has n+m observations, where the researcher uses the first n observations to predict the parameters in the model and saves the last m observations for forecasting. Let f_{n+h} be the one step before the forecast of yn+h+1 for h=0, 1,..., m-1. The m forecast errors are $u_{n+h+1} = y_{n+h+1} - f_{n+h}$. The suitable measures for forecasting in root mean squared error (RMSE)

$$RMSE = \left(m - 1\sum_{n=0}^{m-1} \hat{\mu}^2_{n+h+1}\right)^{\frac{1}{2}} \text{......(9)}$$

This is necessarily the sample standard deviation of the forecast errors. (Wooldridge 2021). If the study figures out the RMSE for two or more forecasting methods, then the study chooses the technique with the smallest out-of-sample RMSE. A second standard measure is the mean absolute error (MAE), which is the average of the absolute forecast errors.

$$MAE = m^{-1}\sum_{n=0}^{m-1}\left|\hat{e}_{n+h+1}\right| \ldots. (10)$$

Again, the study adopts a smaller MAE.

4. Results

4.1. Descriptive Statistics

The logarithmic returns of the NPR-USD exchange rate exhibit characteristics typical of financial time series (Table 1). The near-zero mean (7.99×10^{-5}) and symmetric median (0.0000) reflect stable daily returns, while the standard deviation (0.002589) indicates moderate volatility. The distribution exhibits positive skewness (0.558) and high kurtosis (8.640), suggesting occasional large appreciations and frequent extreme returns. The maximum single-day change was +1.64% (appreciation) and -1.55 % (depreciation).

Table 1: Descriptive Statistics of NPR-USD Returns

Statistic	Value	Interpretation
Mean	7.99×10^{-5}	Near-zero, as expected for returns.
Median	0.0000	Symmetrical around zero.
Maximum	0.016435	Largest single-day appreciation.
Minimum	-0.015541	Largest single-day depreciation.
Std. Dev.	0.002589	Low absolute volatility.
Skewness	0.558*	Right-tailed distribution (positive skew).
Kurtosis	8.640*	Leptokurtic (fat tails, excess peakedness).
Jarque-Bera	5,152.614*	Rejects normality (*p* < 0.01).

4.2. Stationarity Tests

The stationarity of the NPR-USD exchange rate series was examined using both Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests as shown in Table 2. For the level series (raw exchange rates), the ADF test yielded a t-statistic of -2.341 ($p = 0.162$), and the PP test showed -2.295 ($p = 0.175$), failing to reject the null hypothesis of a unit root. This indicates that the series is non-stationary [I(1)]. However, the log return series demonstrated strong stationarity, with highly significant ADF (-62.721, $p = 0.000$) and PP (-62.705, $p = 0.000$) test statistics, rejecting the unit root hypothesis and confirming stationarity [I(0)]. These results validate the common practice of using differenced or log-transformed exchange rate data for volatility modeling, as the transformed series meets the stationarity requirements for reliable econometric analysis while the raw levels do not. The findings support the use of log returns in subsequent GARCH modeling to avoid spurious regression results that could arise from non-stationary data.

Table 2: Stationarity Test Results

Series	ADF t-statistic	PP t-statistic	Conclusion
Level (NPR/USD)	-2.341 (p = 0.162)	-2.295 (p = 0.175)	Non-stationary [I(1)]
Log Returns	-62.721* (p = 0.000)	-62.705* (p = 0.000)	Stationary [I(0)]

4.3. Volatility Clustering and ARCH Effects

The analysis reveals strong evidence of volatility clustering in NPR-USD returns, with distinct periods of high volatility (particularly during 2015-2016 and the 2020 COVID-19 crisis) alternating with calmer periods (such as 2017-2019), as visually apparent in the time series plot in Figure 1. Diagnostic tests statistically confirm this pattern, as the ARCH-LM test strongly rejects the null hypothesis of no ARCH effects (F-statistic = 14.01, $p = 0.0002$), indicating significant heteroskedasticity in the series. Furthermore, the Ljung-Box Q-test applied to squared returns reveals significant autocorrelations up to lag 10 ($p < 0.01$), suggesting that large price movements tend to be followed by similarly large movements. These findings collectively confirm that the NPR-USD exchange rate exhibits the typical volatility clustering phenomenon observed in financial markets, where periods of turbulence and stability tend to persist over time.

Figure 1: Time Series Plot of NRS Exchange Rate Against US Dollars

4.4. Model Estimates

The analysis employed an ARIMA (2,1,2) model to capture the short-term dynamics of NPR-USD returns. This specification includes two autoregressive (AR) terms, first-order differencing, and two moving average (MA) terms. The model equation shows significant coefficients for all terms ($p < 0.05$), indicating strong explanatory power for return movements. Diagnostic checks confirmed the model's adequacy, with Ljung-Box tests on residuals showing no significant autocorrelation ($p > 0.10$), satisfying key modeling assumptions.

The baseline GARCH(1,1) model demonstrated high persistence in volatility shocks ($\alpha + \beta = 0.995$), with both ARCH ($\alpha = 0.036$) and GARCH ($\beta = 0.959$) terms being statistically significant. However, this symmetric specification cannot capture potential asymmetric effects of positive versus negative shocks on volatility.

The Threshold GARCH model revealed significant asymmetry ($\gamma = -0.009$, $p = 0.0046$), indicating that negative shocks reduce volatility more than positive shocks. The model also showed extremely high persistence ($\alpha + \beta = 0.998$), suggesting that volatility shocks take considerable time to dissipate.

The Exponential GARCH specification produced mixed results. While it showed significant ARCH effects ($\alpha = 0.237$), the asymmetry term was insignificant ($\gamma = 0.007$), suggesting this logarithmic formulation may not be ideal for Nepal's exchange rate data. The negative GARCH coefficient ($\beta = -0.240$) raises additional interpretation challenges.

Among the three specifications, TGARCH(1,1) emerged as the preferred model based on (Table 3):

- Superior information criteria (AIC = -9.178)
- Highest log-likelihood value (17,168.85)
- Statistically significant asymmetryterm
- Theoretical relevance to Nepal's managed float regime

Table 3: GARCH Family Model Estimates

Parameter	GARCH(1,1)	TGARCH(1,1)	EGARCH(1,1)
ω (Constant)	4.29×10^{-8}*	4.89×10^{-8}*	-14.941*
α (ARCH)	0.036*	0.041*	0.237*
β (GARCH)	0.959*	0.958*	-0.240*
γ (Asymmetry)	–	-0.009*	0.007 (n.s.)
Persistence (α + β)	0.995	0.998	–
AIC	-9.179	-9.178	-9.094
Log-likelihood	17,167.55	17,168.85	17,009.39

4.5. Forecasting Performance

The study evaluated the out-of-sample forecasting performance of GARCH-family models for the NPR-USD exchange rate from October 2023 to March 2024. Among the tested models, GARCH(1,1), TGARCH(1,1) (dynamic), and EGARCH(1,1), the TGARCH(1,1) dynamic model demonstrated the highest accuracy, achieving the lowest Root Mean Squared Error (RMSE = 0.000755) and Mean Absolute Error (MAE = 0.000457). This represents a 1–2% improvement over the standard GARCH and EGARCH models (Table 4). The TGARCH model's superiority is attributed to its ability to capture asymmetric volatility effects, where negative shocks disproportionately influence future volatility.

Figure 2 further validates these results, showing that the TGARCH forecasts closely track actual volatility, particularly during periods of market turbulence (e.g., early 2024). This robust performance underscores the model's practical utility for the Nepal Rastra Bank (NRB) and financial stakeholders in anticipating exchange rate risks and formulating stabilization policies. The findings align with empirical evidence from emerging markets, where asymmetric models often outperform symmetric ones in volatile regimes.

Table 4: Forecast Accuracy Metrics

Model	RMSE	MAE
GARCH(1,1)	0.000758	0.000460
TGARCH(1,1) Dynamic	0.000755	0.000457
EGARCH(1,1)	0.000761	0.000462

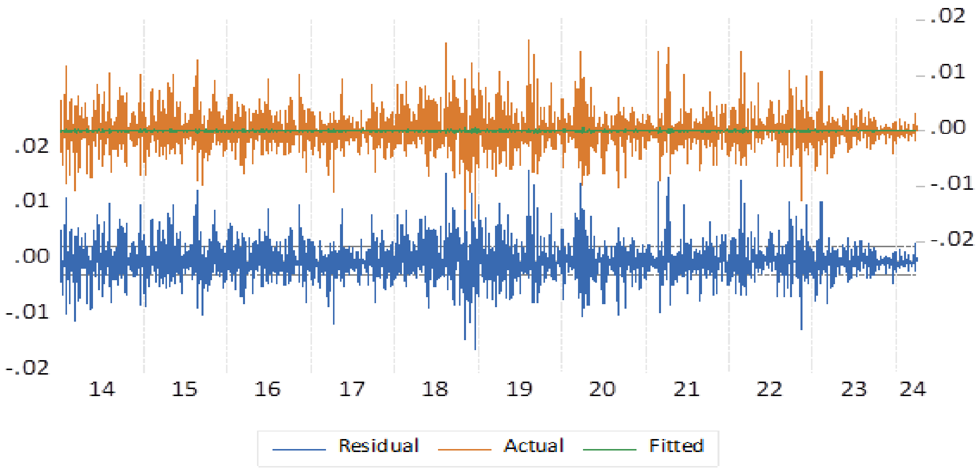

Figure 2: Residual of the Returns Series

5. Discussion

The TGARCH(1,1) model emerged as the best-performing model, exhibiting the lowest AIC (-9.178) and highest log-likelihood (17,168.85), confirming its superior fit compared to GARCH(1,1) and EGARCH(1,1). The significant negative asymmetric coefficient (-0.009, *p* = 0.0046) indicates that negative shocks (e.g., economic downturns or policy uncertainties) reduce volatility more sharply than positive shocks of the same magnitude. This finding supports Black's (1976) leverage effect theory, which concludes that adverse market movements amplify volatility more than favorable ones.Another study found that the adverse market movements can amplify volatility differently, but it does not explicitly state that adverse movements amplify volatility more than favorable ones (Pamba et al. 2025).
Additionally, the high persistence of volatility shocks (sum of ARCH + GARCH coefficients = 0.998) suggests that exchange rate fluctuations in Nepal exhibit long memory effects, consistent with Bollerslev's (1986) GARCH framework. This persistence aligns with studies on other developing economies, such as Alam & Rahman's (2012) analysis of BDT/USD volatility, where GARCH models effectively captured prolonged volatility clustering.
The TGARCH(1,1) dynamic model achieved the lowest forecast errors (RMSE = 0.000755, MAE = 0.000457) in out-of-sample testing (Oct 2023–Mar 2024), outperforming both GARCH and EGARCH. This result is consistent with Hansen & Lunde's (2005) comparison of 330 volatility models, which found that accounting for asymmetries improves forecast accuracy. The model's ability to closely track actual volatility during turbulent periods reinforces its reliability for policymaking and risk management, particularly in Nepal's exchange rate system, which is pegged to the Indian Rupee but floats against other currencies.
Contrary to expectations, the EGARCH(1,1) model showed an insignificant leverage effect coefficient (0.0067, *p* = 0.6079), suggesting that logarithmic volatility transformations may not fully capture Nepal's unique exchange rate dynamics. This contrasts with Nelson's (1991) EGARCH theory, which assumes that positive and negative shocks have distinct logarithmic impacts. A potential explanation is Nepal's dual exchange rate regime, where the NPR-INR peg dampens volatility asymmetries that are more pronounced in free-floating currencies.
While this study provides valuable insights, several limitations should be acknowledged. The analysis relies exclusively on historical exchange rate data, excluding macroeconomic variables such as inflation differentials, interest rates, and remittance flows, which are known to influence currency volatility in Nepal. A univariate framework may therefore overlook important fundamental drivers. Furthermore, the study focuses on the NPR-USD pair. Given that the Nepalese rupee is pegged to the Indian rupee, volatility is inherently influenced by the dynamics of the INR-USD exchange rate. The models presented do not explicitly account for this pivotal transmission channel, which could be a significant factor in the observed volatility patterns. Finally, the findings are specific to Nepal's unique managed exchange rate regime. The generalizability of the results to other developing economies, particularly those with free-floating currencies, may be limited. The identified superiority of the TGARCH model is thus context-dependent and may not hold in different institutional or policy environments.

6. Conclusion

This study found that the TGARCH model is the most effective approach for modelling and forecasting volatility in the NPR-USD exchange rate, outperforming standard GARCH and EGARCH models due to its ability to capture asymmetric responses to market shocks. The findings confirm significant volatility persistence and a leverage effect, in which adverse economic shocks exert a greater influence on exchange rate fluctuations than positive ones. By providing accurate out-of-sample forecasts (RMSE = 0.000755, MAE = 0.000457), the TGARCH model offers the Nepal Rastra Bank a reliable tool to mitigate exchange rate risks and stabilise the currency. Future research should explore multivariate GARCH models that incorporate macroeconomic variables to further enhance predictive precision in Nepal's unique pegged-floating exchange rate regime.

References

Adetunde, I. A., & Appiah, S. T. (2011). Forecasting exchange rate between the Ghana Cedi and the US dollar using time series analysis. *African Journal of Basic & Applied Sciences, 3*(6), 255–264.

Alam, M. Z., & Rahman, M. A. (2012). Modelling volatility of the BDT/USD exchange rate with GARCH model. *International Journal of Economics and Finance, 4*(11), 193–204.

Antonakakis, N. (2007). Forecasting nominal exchange rate volatility in developing and industrialised countries. *Modern Economy, 6*(1), 1–18.

BenSaida, A. (2021). The good and bad volatility: A new class of asymmetric heteroskedastic models. *Oxford Bulletin of Economics and Statistics, 83*(2), 540–570. https://doi.org/10.1111/obes.12398

Black, F. (1976). The pricing of commodity contracts. *Journal of Financial Economics, 3*(1–2), 167–179.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1

Brooks, C. (2008). *Introductory econometrics for finance* (2nd ed.). Cambridge University Press.

Dahal, S. K., & Raju, G. R. (2022). An analysis of the exchange rate regime of Nepal: Determinants and inter-dynamic relationship with macroeconomic fundamentals. *Journal of Asian Finance, Economics and Business, 9*(7), 27–39.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association, 74*(366), 427–431.

Dwarika, N., Moores-Pitt, P., & Chifurira, R. (2021). Volatility dynamics and the risk-return relationship in South Africa: A GARCH approach. *Investment Management & Financial Innovations, 18*(2), 106. http://dx.doi.org/10.21511/imfi.18(2).2021.09

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica, 50*(4), 987–1007.

Epaphra, M. (2017). Modeling exchange rate volatility: Application of the GARCH and EGARCH models. *Journal of Mathematical Finance, 7*(1), 121–143. https://doi.org/10.4236/jmf.2017.71007

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance, 48*(5), 1779–1801.

Hansen, P. R., & Lunde, A. (2005). A forecast comparison of volatility models: Does anything beat a GARCH(1,1)? *Journal of Applied Econometrics, 20*(7), 873–889. https://doi.org/10.1002/jae.800

Ljung, G. M., & Box, G. E. P. (1978). On a measure of lack of fit in time series models. *Biometrika*, 65, 297–303.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica, 59*(2), 347–370.

Pamba, D., Mukorera, S., & Moores-Pitt, P. (2025). The asymmetric effects of cross-border equity flow volatility on equity market returns in SANEK countries. *Quantitative Finance and Economics, 9*(1), 40–75. https://doi.org/10.3934/qfe.2025002

Paudel, R. C., & Burke, P. J. (2015). Exchange rate policy and export performance in a landlocked developing country: The case of Nepal. *Journal of Asian Economics,* 38, 55–63. https://doi.org/10.1016/j.asieco.2015.04.003

Phaju, R. (2021). An analysis of causal relationship between remittances and imports in Nepal. *Economic Journal of Nepal, 44*(1–2), 54–75. https://doi.org/10.3126/ejon.v44i1-2.55027

Thapa, N. B. (1996). *Economic fundamentals and recent changes in exchange rates*. Nepal Rastra Bank Samachar.

Thapa, N. B. (2002). *An econometric analysis of the impact of real effective exchange rate on economic activities in Nepal* (Occasional Paper No. 14). Nepal Rastra Bank.

Tsay, R. S. (2005). *Analysis of financial time series*. John Wiley & Sons.

Vilasuso, J. (2002). Forecasting exchange rate volatility. *Economics Letters, 76*(1), 59–64. https://doi.org/10.1016/S0165-1765(02)00023-0.