Original Article *Journal of Multidisciplinary Research Advancements (JOMRA), Vol. 4, No. 1 (2026), 102 – 115*
e-ISSN 2990-7721 Available online at https://www.nepjol.info/index.php/jomra

Analyzing Stock Volatility in Nepse Index: A Comparative Study between Symmetric and Asymmetric GARCH Models

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Abstract: The stock exchange of each country is the barometer of its economy and plays a vital role in the efficient allocation of scarce financial resources. However, the stock exchange faces conditions of uncertainty and unpredictability, which exhibit volatility. Such characteristics of the stock exchange undesirably affect the financial market. This study examined the volatility pattern of the Nepal Stock Exchange (NEPSE) using the daily return series of the NEPSE index from August 15, 2014, to April 30, 2024. A total of 2218 values were considered for the study. For the study, the ARIMA (1,1,3) model was considered to determine the mean equation, GARCH (1,1) for measuring the conditional volatility, GARCH-M (1,1) for the risk premium, and TGARCH (1,1), EGARCH (1,1), and PGARCH (1,1) to determine the presence of leverage effects on the stock exchange. It was concluded that the Nepalese stock exchange is volatile, exhibiting volatility clustering, indicating that volatility is large, followed by even larger volatility. Additionally, it exhibits both symmetric and asymmetric effects on volatility. GARCH (1,1) and GARCH-M (1,1) models exhibit a symmetric effect, in which the impact of positive and negative shocks on returns is equal. The GARCH-M (1,1) model indicates that the Nepalese stock market does not provide additional returns to investors for taking risks. On the other hand, the TGARCH (1,1), EGARCH (1,1), and PGARCH (1,1) models reveal an asymmetric effect: the negative effect of a shock on returns is larger than the positive effect. The study concludes that the PGARCH (1,1) model best captures the volatility persistence of the daily return series of the NEPSE index.

Keywords: *ARIMA, Risk Premium, Volatility, NEPSE, GARCH Models, Leverage Effect, Volatility Persistence, Asymmetric Effect*

Conflicts of interest: None
Supporting agencies: None

Received 11.02.2026 Revised 19.04.2026 Accepted 12.05.2026

Cite This Article: Dahal, D.K., Gautam, B., Gnawali, B. (2026). Analyzing Stock Volatility in Nepse Index: A Comparative Study between Symmetric and Asymmetric GARCH Models. *Journal of Multidisciplinary Research Advancements, 4(*1), 102-115.

1. Introduction

Most individuals involved in the financial market agree on two essential beliefs. First, the financial market is highly uncertain and is currently experiencing an unprecedented level of volatility. Second, the financial market is full of uncertainties. The complexity of volatility lies in its interpretation, as it means different things to different people, making discussion vague. Furthermore, a great deal of misleading information surrounds the concept. Volatility, as an essential tool for measuring statistical risk, is an instrument used to assess market risk for both specific financial items and groups of items in a portfolio.

In other words, volatility is the measure of the variability in the average price of financial securities like shares, bonds, government securities, and currencies noticed during a particular period. Furthermore, it is defined as the measure of the variability in the price of the security or commodities during a short period (Mullins, 2000). Volatility is associated with the variety of possible outcomes for impulsive variables. Hence, volatility often defines the level of uncertainty or risk associated with the change in the value of the asset. This means that high volatility is associated with the risk of the change in the price of the asset during a short period in any direction, while low volatility is associated with the consistent and lesser influenced change in the value of the asset. Furthermore, it is defined as the statistical measure of the value of the change in the returns during a particular asset or the overall asset index. This measure can be determined by the use of the standard deviation or variance of the returns of the asset. It is often associated with high risk during the asset.

In the financial sphere, the emphasis is on the outcome of asset returns. Volatility has been connected with the sample standard deviation of the returns obtained over a definite time span. Market participants are found to be highly vigilant when the stock prices are declining or are going through a 'correction' phase. In an unusually high bull market, the majority of people are indifferent to the existence of volatility. Volatility exists in the market if there are considerable and wide-ranging changes in the prices of the securities or the returns earned on them over a definite time span. In a stable market, the prices are found to be following a gradual course, smoothly changing from one equilibrium point to another as the information is absorbed slowly into the prices. Volatility, in essence, can be stated as the extent to which the prices of the assets are fluctuating substantially, reflecting the extent of the rise and fall.

A stock market is considered a volatile market when there are sharp inclines and declines in the market over a short period of time. “The assessment of stock return volatility is the evaluation of the unpredictable changes occurring in the stock return. In a nutshell, the stock return volatility fundamentally measures the changes occurring in the stock return over a given period of time.” Although the volatility of the stock return can be explained using a number of methods, the standard deviation is the most commonly used to define the volatility. It measures the degree to which the current price varies from the average over a given period of time. As the degree of variation increases, the volatility also increases. As a result, the determination of the future value of a highly volatile stock becomes increasingly complex. It states the standard deviation of daily stock return to mean, and the volatility of the stock market fundamentally indicates the return volatility of the entire market portfolio.

The large fraction of society understands that the term volatility is associated with the term risk, and they strongly believe that high volatility is not acceptable because the prices of the securities are unreliable, which indicates that the capital markets are not functionally well. Merton Miller, a Nobel laureate in economics (1990), states in his book "Financial Innovation and Market Volatility" that people often define the term volatility as the days with noticeable movements in the stock markets, particularly downwards, without a particular reason. It is common to see in the stock markets, where the prices of the stocks are based on the personal judgment of the individual for the cash flows to be generated in the future and the selling price of the stock, opposing this complex dynamism of the stock markets, people often try to guess the particular reasons responsible for the downfall of the markets, overviewing the inherent uncertainty character of the asset values. Schwartz (1989) recommended that the term volatility represents the fluctuation or unpredictability of the asset values. In theory, when the cash flow of the discount rates becomes more volatile, the stock prices become volatile. Moreover, phenomena like 'fads' or 'bubbles' contribute extra volatility to the market. Price fluctuation is the crucial element of volatility not a direction of change. Whether there is fluctuation in price or remains flat, the fluctuation in price could be consistent irrespective of the direction of the trend.

Measuring volatility is of great importance to different individuals in the market for many reasons. The pricing of securities is based on the volatility of each security. Mature markets have lower volatility but offer high returns in the long term. Contrary to this, in emerging economies, except India and China, most economies have lower returns, some even negative, with high volatility (Porwal and Gupta, 2006). The Nepalese capital market began in 1976 with the establishment of the Securities Marketing Center (SMC), which was later transformed to the Securities Exchange Center (SEC) in 1984 after the approval of the Securities Exchange Act. The SEC was responsible for overseeing trading, brokerage, underwriting, and managing shares and government securities. In 1993, the SEC was fragmented into the Securities Board of Nepal (SEBON) and Nepal Stock Exchange Limited (NEPSE). SEBON oversees the development and supervision of the market, and NEPSE is responsible for authorizing trading of securities.

2. Methodology

2.1. Research Design

The concept of research design has been recognized as a base for conducting research, considering aspects like the selection of research questions, pertinent data, data collection, and analysis of results. The current research employs a longitudinal time-series research design using secondary daily data. This design is appropriate because it examines the dynamic patterns of volatility in the NEPSE index over a ten-year period without manipulating any variables.The research has been conducted in a descriptive manner, considering an empirical model-based research design for assessing the dynamic process of the volatility model.

2.2. Nature and source of Data

This research mainly relies on secondary data sources based on the closing data of the NEPSE index. The historical series data for the purpose of the research are obtained from the official websites of the NEPSE, SEBON, and NRB. Other data are collected from different sources like books, journals, newspapers, and the internet. The data are adequate for performing meaningful time series analysis by employing different volatility models.

Generally, the data of the financial time series are found to follow lognormal distribution, which means the logarithmic transformation of the data is normally distributed. Hence, the change in the relative price is naturally measured by the comparison of the logarithmic price. The difference is generally referred to as log relatives, which are normally distributed (Black and Scholes, 1973).

This research aims to measure the volatility based on returns (R_t), which is the natural logarithm of the index relatives:
Rt=log⁡e(ItIt−1)R t =log e (I t−1I t) (3.1)

In this equation, R_t represents the continuous daily return at time t, while I_{t-1} and I_t denote the daily closing indexes of the stock on two consecutive days, t-1 and t, respectively.

2.3. Study Period

The research utilizes the data of the daily closing index of NEPSE for 10 years with 2218 observations ranging from August 15, 2014, to April 30, 2024, as the NEPSE introduced electronic trading of securities for the first time.

2.4. Tools for Data Analysis

The analysis of the research is done by employing the EVIEWS 13 package after the data collection. The subsequent sections of the research discuss the different econometric and statistical techniques employed in the research.

2.5. Data Extraction and Synthesis

This research has adopted different statistical tools and methods for data analysis. Hence, the research incorporates descriptive statistics, which include the calculation of mean, median, maximum, minimum, standard deviation, skewness, kurtosis, and the Jarque-Bera test. The research also incorporates unit root tests, correlogram, ARIMA, and heteroskedasticity tests.

2.6. Unit Root Test

Firstly, the study considers the stationarity of the time series with reference to the fluctuations of the index. Engle and Granger (1987) found that some time series variables exhibit non-stationarity or different degrees of integration. It has been found that conventional regression methods can be used for non-stationary time series, which results in spurious regression, as found by Nelson and Plosser (1982) and confirmed by Stock and Watson (1988). Hence, the Augmented Dickey Fuller test and the Phillip-Perron test are conducted for the stationarity of the series.

2.7. Augmented Dickey-Fuller (ADF) Test

The Augmented Dickey-Fuller test, which was first introduced by Dickey and Fuller in 1979, implicitly considers the statistical independence and homoscedasticity of the errors. Although heteroskedasticity does not affect a broad range of unit roots test statistics, the problem arises when the estimated residual εt shows evidence of autocorrelation, which makes the test invalid. The random walk process represents a prominent example of the presence of a unit root. The three types of ADF tests are given by the following equations:

$\Delta Yt = \Upsilon_1 Yt_{-1} + \Sigma\beta i\Delta Yt_{-i} + \varepsilon_t$ (3.2)
$\Delta Yt = \alpha_0 + \Upsilon_1 Yt_{-1} + \Sigma\beta i\Delta Yt_{-i} + \varepsilon_t$ (3.3)
$\Delta Yt = \alpha_0 + \Upsilon_1 Yt_{-1} + \alpha_1 t + \Sigma\beta i\Delta Yt_{-i} + \varepsilon_t$ (3.4)

In cases where ε_t is represented as white noise, the incorporation of more lagged differences is determined by selecting the minimum number of residuals without autocorrelation. The tests assume that the null hypothesis (H_0) is that Yt is integrated of order zero, i.e., it is not integrated. When the ADF test statistics are found to be lower than the critical values, the null hypothesis (H_0) is accepted, implying that the series is non-stationary.

2.8. Phillips-Perron (PP) Test

The Dickey-Fuller tests are based on the assumption that the residual terms indicate statistical unconventionality and that the variance remains consistent. Phillips and Perron (1988) developed an extension of the methodology for the ADF test, which enabled the imposition of only modest conditions on the distribution of the errors. The PP regression equations are identical to the ADF regression equations. In the case of the ADF test, the higher-order serial correlation is addressed by the inclusion of lagged differenced terms, while the t-statistic for the coefficient γ in the PP test is adjusted for the serial correlation in ε_t. Therefore, the ADF and PP tests are both used for the purpose of determining the stationarity of the data.

2.9. Correlogram

The correlogram can be obtained by creating the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, which are the most significant for the ARMA/ARIMA model detection. The plots for the ACF and PACF allow for the investigation of the time series data, which might be trending, seasonal, and correlated. Therefore, the correlogram can be plotted for the purpose of identifying the application of the ARMA/ARIMA model for further volatility analysis.

2.10. Auto-Regressive Moving Average (AMRA)

The ARMA model or ARIMA model is also referred to as the Box-Jenkins methodology developed by George E.P. Box and Gwilym M. Jenkins in 1970, which is generally used to investigate and forecast the time series data. The ARMA model is generally a univariate model where the past dependent variable explains the current variable. Hence, the ARMA model is developed by combining AR and MA components.

2.11. Heteroscedasticity Test

However, before employing the GARCH model, it is essential to check whether the residuals have changing variance, i.e., the heteroscedasticity test. The current study employs the heteroscedasticity test for ARCH to check for the presence of autocorrelation in the residuals. This will inform us whether the variance of the residuals changes with time, i.e., heteroscedasticity. The tests will determine whether the data can be modeled using the GARCH model, as it is designed to handle changing volatility. After employing the GARCH model, it is essential to carry out tests to ensure the correct model is employed.

2.12. Model Specification

This study employs the various volatility models including simple GARCH, GARCH-M, TGARCH, EGARCH, and PGARCH models to identify the presence of volatility persistence and asymmetric effects.

2.13. ARCH Model

The Autoregressive Conditional Heteroscedasticity (ARCH) model is a statistical model that has been used for modeling the squared error terms of time series data based on the magnitude of the previous period's squared error terms. Wang (2009) suggested that ARCH models can be used for representing and capturing some stylized facts that are realized from the volatility of financial time series, for example, the varying levels of volatility. Autocorrelation that exists in the squared returns, also known as conditional heteroskedasticity or volatility clustering, can be addressed by modeling an ARMA model for squared returns.

2.14. The Symmetric GARCH Models

The generalized Autoregressive Conditional Heteroskedasticity (GARCH) model was originated by Bollerslev in 1986. It referred to the extension of the original version of the ARCH model by Engle to abridge the model by reducing the number of parameters to enable better computation. Thus, the GARCH model is a technique of encompassing the variances to forecast the variances.

Simple GARCH Model: Bollerslev extended the ARCH model developed by Engle (1982), which is considered to be the GARCH model. A symmetric GARCH (SGARCH) model demonstrates the symmetric impact of the GARCH model. It shows that positive and negative shocks have the same impact on the return series. It is described by:

Mean equation: $y_t = \alpha + \beta' X_t + \varepsilon_t$ (3.14)
Conditional variance equation: $\sigma_t^2 = \alpha_0 + \Sigma\alpha_i\varepsilon_{t-i}^2 + \Sigma\beta_j\sigma_{t-j}^2$ (3.15)
GARCH-in-Mean (GARCH-M) Model: The GARCH-in-Mean model includes the conditional variance into the conditional mean equation. It is expressed as:
$y_t = \alpha + \beta' X_t + \lambda\sigma_t + \varepsilon_t$ (3.16)

2.15. Asymmetric GARCH Models

Asymmetric GARCH model takes into account the asymmetry of the volatility, which means the impact of negative and positive shocks is different.

GJR-GARCH Model/TGARCH: Golsten, Jagannathan, and Runkle (1993) introduced the model. The generalized GJR-GARCH (p,q) model: $\sigma_t^2 = \alpha_0 + \Sigma(\alpha_i + \gamma_i I_{t-i})\varepsilon_{t-i}^2 + \Sigma\beta_j\sigma_{t-j}^2$ (3.17)
where $I_{t-i} = 1$ if $\varepsilon_{t-i} < 0$, and 0 otherwise.
EGARCH Model: The exponential GARCH model introduced by Nelson (1991) focuses on asymmetric volatility effect. It assumes the logarithm of variances [$\ln(\sigma^2)$] and is expressed as:
$\ln \sigma_t^2 = \alpha_0 + \Sigma\alpha_i[|\varepsilon_{t-i}|/\sqrt{\sigma_{t-i}^2} - \sqrt{(2/\pi)}] + \Sigma\gamma_i(\varepsilon_{t-i}/\sqrt{\sigma_{t-i}^2}) + \Sigma\beta_j \ln \sigma_{t-j}^2$ (3.19)
PGARCH Model: Ding, Granger, and Engle (1993) introduced the Power GARCH model to capture asymmetric response of volatility. The general form is: $\sigma_t^d = \alpha_0 + \Sigma\beta_j\sigma_{t-j}^d + \Sigma\alpha_i\varepsilon_{t-i}^2 + \Sigma\eta_i(|\varepsilon_{t-i}| + \gamma_i\varepsilon_{t-i})^d$

2.16. Estimation of GARCH Models

The traditional Ordinary Least Square (OLS) technique is not applicable in these cases. The Maximum Likelihood approach is carried out in these cases, which works with the GARCH model in order to determine the best possible parameters for the data.

2.17. Maximum Likelihood Estimation (MLE)

While the parameters are being estimated with the help of MLE, the model needs to be a parametric model, i.e., it needs to be completely specified by the joint probability density function. If the time series data, i.e., $y_1, y_2, ..., y_t$, are independent and identically distributed, then the log-likelihood function can be expressed as: $\text{Log}(y,\theta) = \Sigma\, p(y_t)$ (3.22)
where θ is the parameters of the model. The MLE of θ maximizes the likelihood function.

2.18. Hypothesis Testing

This study conducts three hypotheses:
Hypothesis 1 (Volatility Persistence): In this hypothesis, the study uses various GARCH models to fit the data and check the value of the coefficient of the ARCH and GARCH terms, and if the coefficients are significant, then it shows the presence of volatility persistence.
Hypothesis 2 (Leverage Effect): In this hypothesis, the study uses asymmetric models of GARCH, namely TGARCH, EGARCH, and PGARCH, to estimate the effects, and if the effects are significant, then it shows the presence of leverage effects.
Hypothesis 3 (Model Selection Criterion): In this hypothesis, after estimating the parameters, the study uses the Akaike Information Criterion and Log-likelihood statistics to select the best model for volatility persistence.

3. Results

3.1. Data Transformation and Preliminary Analysis

The research process began by converting the daily NEPSE index series into a return series by applying the logarithmic transformation as follows: $\text{Return}_t = \log(\text{NEPSE}_t/\text{NEPSE}_{t-1})$. Figure 1 displays the daily return series resulting from this conversion process from August 15, 2014, to April 30, 2024, totaling 2218 observations. The resulting return series displays the general features of financial time series data, which include periods of high volatility followed by periods of high volatility and so on.

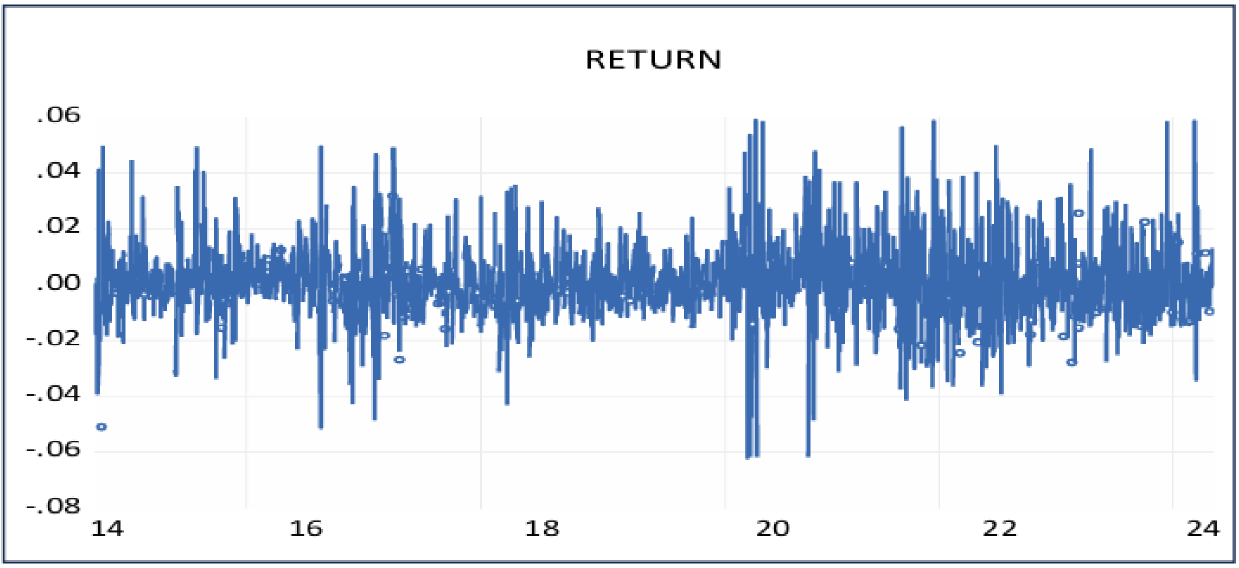

Figure 1: Daily Returns Series of NEPSE Index (August 15, 2014 – April 30, 2024)

3.2. Descriptive Statistics

The descriptive statistics for the NEPSE daily returns series have been shown in Figure 2. The mean for the returns series is around 0.000308, which reflects a relatively low average return for the data series. The median for the returns series is around -0.0043, which reflects marginally negative returns for the data series. The maximum and minimum returns for the data series are 0.05886 and -0.062287, respectively, which reflect significant positive and negative returns for the data series. The standard deviation for the returns series is 0.013404, which reflects the average deviations from the mean and defines the volatility for the data series.

The skewness for the returns series is around 0.324793, which reflects a marginally positive skewness for the data series, indicating that positive returns have a higher frequency or magnitude than negative returns. The kurtosis for the returns series is around 6.009297, which reflects a leptokurtic distribution for the data series since it is significantly higher than 3, which is the kurtosis for a normal distribution. The Jarque-Bera statistic for the returns series is around 875.5145 with a p-value of 0.000000, which reflects that the data series significantly deviates from a normal distribution. These indicators collectively demonstrate that the daily return series exhibits non-normality, leptokurtosis, and potentially significant volatility, justifying the application of advanced GARCH modeling techniques.

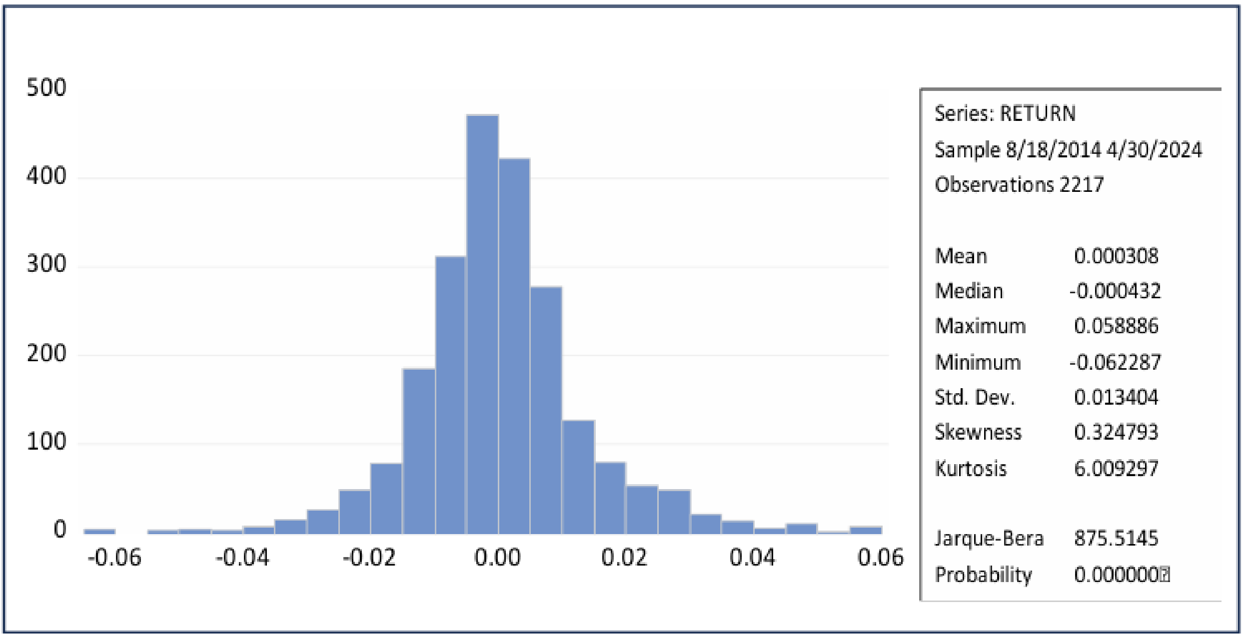

Figure 2: Descriptive statistics of NEPSE Daily Return Series

3.3. Stationarity Tests

Before proceeding with the modeling, it is vital to check the data for stationarity. The research utilized Augmented Dickey Fuller (ADF) and Phillips Perron tests, and the results are shown in Table 1.

Table 1: Unit Root Tests (ADF and PP Tests)

Test	Test Statistic	Probability	Critical Value (1%)	Critical Value (5%)	Critical Value (10%)
Augmented Dickey-Fuller (ADF)	-25.4706	0.0000	-3.4331	-2.8626	-2.5674
Phillips-Perron (PP)	-41.5234	0.0000	-3.4331	-2.8626	-2.5674

Both ADF and PP test statistics are significant at a 1% level, as their p-values are 0.0000, thus rejecting the null hypothesis of non-stationarity, thereby supporting the fact that the return series is stationary and hence can be subjected to further analysis.

3.4. ARIMA Model Selection

In order to determine a proper equation for the determination of the mean, various ARIMA models were examined in the study, and the selection of a proper ARIMA model was based on the correlogram of ACF and PACF functions, in which it was found that the functions started to decline after the first lag, and the functions declined completely after 3 lags.

Table 2: ARIMA (p, d, q) Model Estimation

ARIMA (p,d,q) Model	AIC	Adjusted R^2	SIGMASQ	Log Likelihood	Significant Coefficient
(1,1,1)	-5.8057	0.0207	0.000176	6439.617	Significant
(1,1,0)	-5.8011	0.0158	0.000177	6433.564	Significant
(0,1,1)	-5.8034	0.0180	0.000176	6436.089	Significant
(2,1,0)	-5.8049	0.0204	0.000176	6439.745	Insignificant
(0,1,2)	-5.8053	0.0204	0.000176	6439.243	Significant
(0,1,3)	-5.8055	0.0210	0.000175	6440.423	Insignificant
(1,1,3)	-5.8071	0.0230	0.000175	6443.174	Significant
(3,1,3)	-5.8058	0.0226	0.000175	6443.785	Insignificant

Out of all the models considered, ARIMA (1,1,3) was found to be the best fit, as it had the lowest AIC (-5.8071), the highest adjusted R^2 (0.0230), a higher log likelihood (6443.174), and significant values. The results of the estimation of this model are presented in detail in Table 3.

Table 3: Estimation of ARIMA (1,1,3) Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.00030	0.00038	0.8112	0.4173
AR (1)	0.8360	0.0886	9.4401	0.0000
MA (1)	-0.6981	0.0859	-8.1225	0.0000
MA (2)	-0.1650	0.0210	-7.8513	0.0000
MA (3)	0.0768	0.0158	4.8492	0.0000
SIGMASQ	0.00017	3.36E-06	52.1290	0.0000
Statistic	Value			
R-squared	0.0252			
Adjusted R-squared	0.0230			
S.E. of regression	0.0132			
Sum squared resid	0.3880			
Log-likelihood	6443.174			
Akaike info criterion	-5.8071			
Schwarz criterion	-5.7916			
Hannan-Quinn criterion	-5.8015			
F-statistic	11.4448			

Prob(F-statistic)	0.0000
Durbin-Watson stat	1.9991

From the ARIMA (1,1,3) estimation, it is evident that the constant term is not statistically significant. On the other hand, the AR(1) term and the MA(1), MA(2), and MA(3) terms are statistically significant. The variance of residuals, denoted as SIGMASQ, is highly statistically significant. The DW is close to 2, suggesting no serial correlation in the residuals. The F-test proves that the model is statistically significant. The model's stability is ascertained by testing the roots of AR/MA polynomials, and they lie within the unit circle.

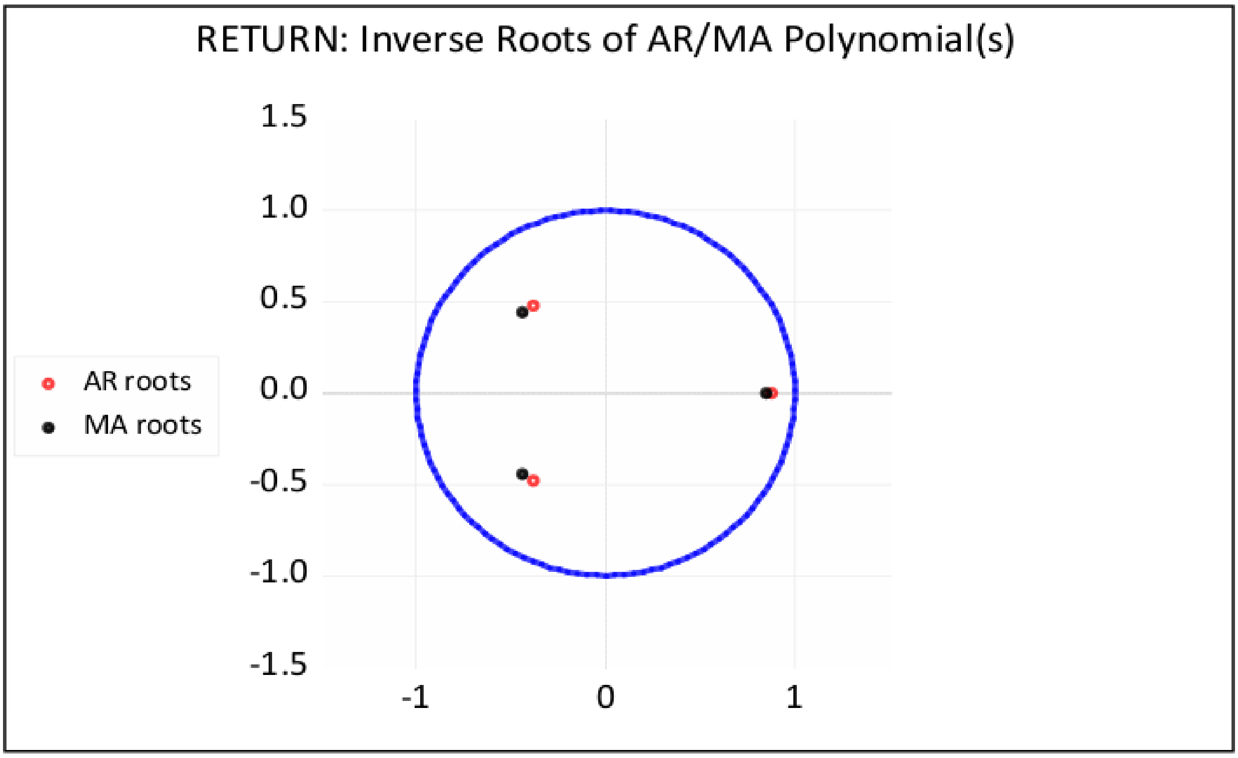

Figure 3: Inverse Roots of AR/MA Polynomials Showing Model Stability

3.5. Volatility Clustering and ARCH Effects

The existence of volatility clustering has also been visually confirmed in the residual plot (Figure 4), which shows that high volatility is followed by high volatility, and low volatility is followed by low volatility. This pattern is a clear visual representation that volatility clustering, or ARCH effects, exists in the data.

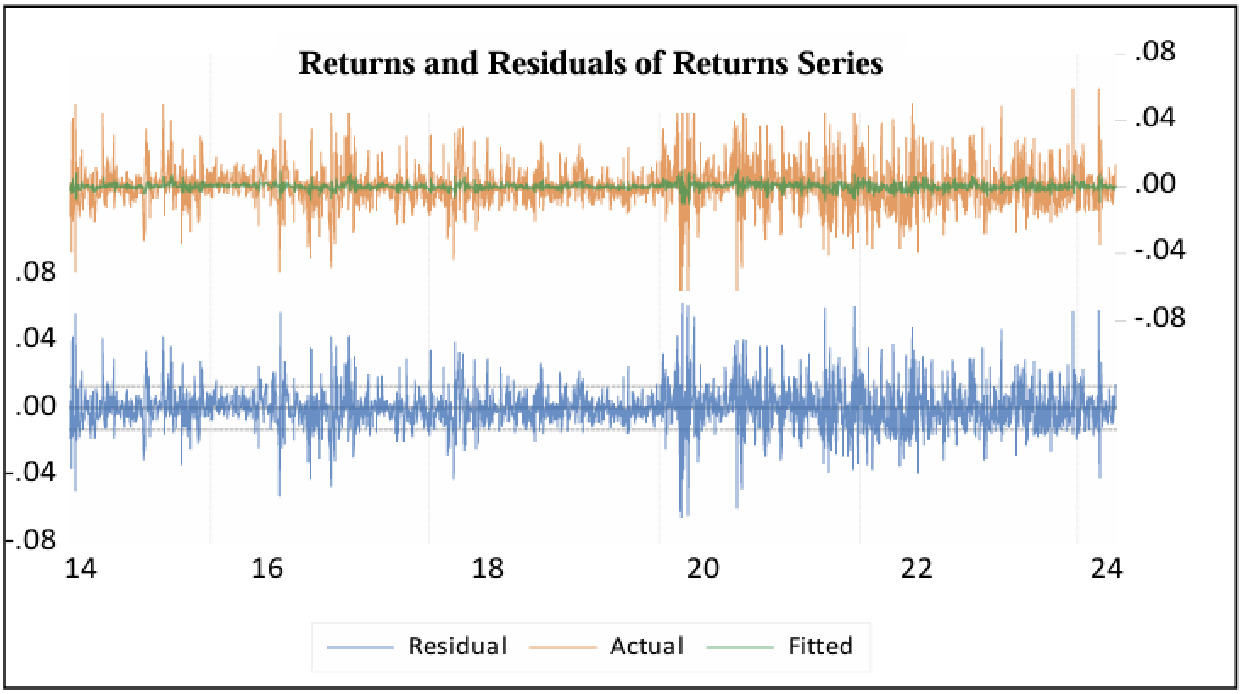

Figure 4: Residuals of Return Series Showing Volatility Clustering

The results obtained from the heteroskedasticity test, as presented in Table 4, validate the results for the presence of ARCH effects. This can be justified with the high value of the F-statistic, which is equal to 216.2943 with a p-value of 0.0000, validating the presence of a significant relationship between squared returns and variance residuals. This justifies the use of GARCH family models for modeling the time-varying volatility in the NEPSE return series.

Table 4: Heteroskedasticity Test

Statistics	Value	Probability
F-statistic	216.2943	Prob. F (1,2214) 0.0000
Obs*R-squared	197.2223	Prob. Chi-Square (1) 0.0000

3.6. Estimation of Symmetric GARCH Models

GARCH (1,1) Model Results

The GARCH (1,1) model was employed to capture the persistence of volatility in the NEPSE stock market returns series. From the variance equation results, it is evident that the ARCH and GARCH terms are significant at the 5% level of significance. The ARCH term is 0.2216, while the GARCH term is 0.7142. The sum of the ARCH and GARCH terms is 0.9358, which is less than one. This fulfills the stationarity condition of the GARCH model. The sum of the ARCH and GARCH terms is very close to one, which indicates high persistence of volatility in the NEPSE stock market returns series. This implies that the effect of current volatility will persist for a long period of time and will not completely die out over time. The results show that current volatility is heavily affected by past volatility, which confirms the presence of volatility clustering and persistence in the NEPSE stock market returns series

GARCH-M (1,1) Model Results

The GARCH-in-Mean model includes the effect of conditional variance into the mean equation to explain the risk-return trade-off. From the estimation results, the sum of ARCH and GARCH parameters is 0.9395 (0.2286 + 0.7109); this indicates high volatility persistence. The risk term (λ) included in the mean equation is positive (0.0379) but found statistically insignificant at 0.6304. This result suggests that an increase in risk does not necessarily lead to an increase in returns in the Nepalese stock market. The GARCH-M model results indicate that investors do not gain any additional returns (risk premium) for taking high risks in the Nepalese stock market, which contradicts the traditional theory of the risk-return trade-off.

Estimation of Asymmetric GARCH Models

The positive skewness observed in the descriptive statistics (0.3248) suggested the presence of asymmetric effects in the returns, justifying the application of asymmetric GARCH models.

TGARCH (1,1) Model Results

The results of the estimation of the Threshold GARCH model show that the coefficient of asymmetry (γ) is positive (0.1283) and statistically significant (p-value = 0.0000). This shows that the negative shocks have a bigger impact on the volatility than the positive shocks. The sum of the ARCH and GARCH coefficients is 0.8792 (0.1503 + 0.7289). This is less than one, which shows high volatility. The results have shown the leverage effects in the Nepalese stock market, which means the negative shocks have a bigger impact on the volatility than the positive shocks.

EGARCH (1,1) Model Results

The results from the estimation of the Exponential GARCH model indicate that the value of the asymmetric coefficient (γ) is negative, i.e., -0.0584, and statistically significant at 0.0003. In the EGARCH model, the negative value of the asymmetric coefficient confirms the existence of leverage effects, which indicate that the market reacts more significantly to negative news compared to positive news. This also confirms the results that the market reacts more significantly to negative news. The value of the persistence coefficient (β) is 0.8781, while the ARCH coefficient (α) is 0.4523. The EGARCH model also confirms the asymmetric volatility behavior of the returns on the NEPSE index.

PGARCH (1,1) Model Results

The Power GARCH model, which accounts for non-linear effects of past and current volatility, was applied, and the power term (d) was found to be 2.1152. The asymmetric effect coefficient (γ) is positive (0.1513) and statistically significant, indicating a p-value of 0.0000, thereby supporting the existence of leverage effects in the Nepalese stock market. The sum of the ARCH and GARCH coefficients is 0.9370, which is less than 1, indicating a high level of volatility persistence in the Nepalese stock market. The persistence parameter ($\alpha + \beta = 0.9370$) implies that the half-life of a volatility shock is approximately 10.65 days, calculated as $\ln(0.5)/\ln(0.9370)$. This means that half of the impact of a shock dissipates after about 11 trading days. Therefore, the significant coefficients and appropriate power term imply the presence of long-run memory in the volatility of the Nepalese stock market.

Comparison of GARCH Models

To identify the most suitable model for capturing volatility dynamics in the NEPSE index, all estimated models were compared using information criteria and log-likelihood values. Table 5 presents the comprehensive comparison.

Table 5: Comparison of GARCH Models

Model	GARCH (1,1)	GARCH-M (1,1)	TGARCH (1,1)	EGARCH (1,1)	PGARCH (1,1)
C	1.34E-05	1.30E-05	1.28E-05	-1.4192	7.06E-06
P-value	0.0000	0.0000	0.0000	0.0000	0.4250
ARCH Coefficient	0.2216	0.2285	0.1503	0.4523	0.2095
P-value	0.0000	0.0000	0.0000	0.0000	0.0000
GARCH Coefficient	0.7142	0.7109	0.7289	0.8780	0.7274
P-value	0.0000	0.0000	0.0000	0.0000	0.0000
Asymmetric Coefficient	-	-	0.1283	-0.0583	0.1512
P-value	-	-	0.0000	0.0003	0.0000
Adjusted R-Square	0.0174	0.0148	0.0180	0.0158	0.0164
AIC	-6.0294	-6.0320	-6.0373	-6.0359	-6.0392
Log-Likelihood	6688.607	6692.508	6698.412	6696.787	6701.468

The comparison shows that all the models have statistically significant ARCH and GARCH coefficients, which proves the presence of volatility persistence in the NEPSE stock exchange index. All the asymmetric models, namely TGARCH, EGARCH, and PGARCH, have statistically significant asymmetric coefficients, which proves the presence of leverage effects in the Nepalese stock exchange. However, the asymmetric coefficients of the TGARCH and PGARCH models are positive, whereas the asymmetric coefficient of the EGARCH model is negative. All the models consistently prove the fact that the Nepalese stock exchange reacts more to negative shocks compared to positive shocks of the same magnitude. On the basis of the selection criteria, the PGARCH (1,1) model appears to be the best fit to explain the conditional variance of the Nepalese stock exchange. It has the minimum Akaike information criteria of -6.0392 and the maximum log likelihood of 6701.468. In addition, the sum of the ARCH and GARCH coefficients of the PGARCH model is 0.9370, which is less than one. It proves that the Nepalese stock exchange exhibits high volatility persistence, with the impact of shocks on the stock exchange lasting a long time. This high persistence indicates that the Nepalese stock market does not function efficiently, as volatility shocks have long-lasting effects on future returns

3.7. Diagnostic Tests for the Selected Model

Having identified PGARCH (1,1) as the most suitable model, a test was carried out to confirm the adequacy of the model in describing the behavior of the volatility. The Ljung-Box Q-statistics test on the squared residuals indicated that the autocorrelation and partial autocorrelation values are small, implying that the p-value is greater than the 5% significance level. Additionally, a test of heteroscedasticity for the presence of ARCH effects was carried out as shown in Table 6.

Table 6: Heteroskedasticity Test of PGARCH (1,1) Model

Statistic	Value	Probability
F-statistic	1.7427	Prob. F (1,2213) 0.1869
Obs*R-squared	1.7429	Prob. Chi-Square (1) 0.1868

4. Discussion

The results show that the Nepalese stock market has high volatility persistence, as the ARCH and GARCH coefficients are close to one for all the models. This is evident by the results, where the sum of the ARCH and GARCH coefficients is close to one for all the models. (GARCH=0.9358, PGARCH=0.9370). This shows that the volatility shocks have long-lasting effects and decay gradually. This is in line with the Efficient Market Hypothesis (Fama, 1970). The Efficient Market Hypothesis argues that new information affects the stock price, which results in the volatility persistence.

This high volatility persistence is in line with the results obtained by various research papers on the stock markets of developed and emerging markets. Bollerslev, Chou, and Kroner (1992) found the same results for the markets. Mala and Reddy (2007) found high volatility in the emerging markets of Fiji. Gokcan (2000) found high volatility persistence in the emerging markets of seven different countries. The results are in line with the results obtained by various research papers for the Nepalese stock exchange. The results are in line with the results obtained by G.C. (2008), Thapa (2012), Thapa and Gautam (2016), and Rana (2020).

The persistence parameter being less than one satisfies stationarity, indicating that while shocks persist, they eventually die out. Poon and Granger (2003) suggested that high persistence in emerging markets is frequently attributed to market inefficiencies and less experienced investors, which accurately characterizes Nepal.

The GARCH-M (1,1) model reveals that the risk term is positive (0.0379) but statistically insignificant (p=0.6304). This indicates that higher risk does not necessarily yield higher returns in Nepal, contradicting the traditional risk-return trade-off theory. Investors do not receive additional compensation for bearing higher risk.

Harvey (1995) argued that emerging markets tend to have different risk-return profiles because of the inefficient markets, lack of diversification, and higher levels of manipulation. This supports the study by Thapa and Gautam (2016) who concluded that the Nepalese stock exchange does not offer a risk premium. Akhtar and Khan (2016) also arrived at a similar conclusion for the Karachi Stock Exchange.

All the asymmetric GARCH models indicate the presence of leverage effects. From the TGARCH model, the asymmetric coefficient is positive and statistically significant at 0.1283 with a p-value of 0.0000. For the EGARCH model, the asymmetric coefficient is negative and statistically significant at -0.0584 with a p-value of 0.0003. For the PGARCH model, the asymmetric coefficient is positive and statistically significant at 0.1512 with a p-value of 0.0000. All the models indicate the presence of leverage effects, which means that negative shocks affect the volatility more than positive shocks of the same magnitude.

This supports the theory of leverage effects developed by Black (1976) that negative shocks affect the volatility of the stock prices because of the increasing levels of uncertainty. As stock prices fall, the debt/equity ratio also increases, thus increasing the volatility. Christie (1982) and Schwert (1989) later suggested that other factors such as interest rates and macroeconomic indicators also play important roles.

This may also be supported by prospect theory (Kahneman & Tversky, 1979), which indicates that investors are prone to loss aversion, where losses are twice as costly as gains. This leads to market behavior where negative news has a greater impact on market volatility.

Evidence of leverage effects in Nepal is supported by other emerging markets as well. Akhtar & Khan (2016) reported significant leverage effects on the Karachi Stock Exchange. Ali (2016) confirmed the asymmetric effect on Indian BSE and NSE stock exchanges. Vasudevan & Vetrivel (2016) reported that asymmetric GARCH models performed better on BSE-SENSEX stock exchange compared to symmetric models. Atoi (2014) reported leverage effects on the Nigerian stock exchange. Sharma et al. (2021) reported significant leverage effects on major emerging markets.

However, these findings differ from earlier research conducted in Nepal. In the research conducted by G.C. (2008), it was found that there was no remarkable asymmetric effect, while in the research conducted by Rana (2020), it was concluded that asymmetric models did not perform well in terms of leverage effects. These differences might be attributed to the fact that more recent data might have accounted for the changing market environment and the sophistication that has taken place since the introduction of electronic trading.

The PGARCH (1,1) model has been identified as the best-fitting model for measuring the conditional variance of the Nepalese stock market, with the lowest AIC (-6.0392) and the highest log likelihood (6701.468). The combined sum of the ARCH and GARCH coefficients (0.9370) indicates high volatility persistence with effects dying out after 10.65 days. This persistence parameter translates to a half-life of approximately 10.65 days for a volatility shock.

The superiority of PGARCH can be attributed to its ability to capture long memory properties and asymmetry simultaneously. Ding et al. (1993) developed the PGARCH model with the aim of capturing markets that show long memory properties and asymmetry simultaneously.

This result is consistent with Thapa and Gautam (2016) for the case of Nepal, Akhtar and Khan (2016) for the case of Karachi, Haniff and Pok (2014) for the case of Malaysia, and Atoi (2014) for the case of Nigeria.

However, there are differing opinions regarding the best model for each market. Gokcan (2000) found GARCH to perform better for emerging markets, while Yu (2002) found stochastic volatility models to perform better for the case of New Zealand, while Alberg et al. (2008) found EGARCH to perform better for the case of Israel.

Despite the asymmetric volatility, the Nepalese market has received some positive shocks that have affected its performance. These include political stability and better governance (Dangal and Gajurel, 2021), financial literacy promotion by the central bank, an increase in NRNs' investments that added liquidity to the market, continuous remittances received by the market that boosted household investment, technological progress achieved by the NEPSE Online Trading System (NOTS), mergers and acquisitions that strengthened the market ecosystem, and economic growth after the COVID-19 pandemic. All these observations indicate that although the market is more sensitive to negative news, it is not entirely unresponsive to positive structural changes, which is a reflection of the complex behavior of emerging markets.

The rate of decay of volatility shocks is relatively low at 10-15 days, implying that the Nepalese stock exchange is not fully efficient in processing information. This is mainly attributed to institutional hold percentages being low, a large number of retail investors with varying financial literacy levels, information asymmetry, regulatory environment, and technology. Bekaert & Harvey (1997) argued that emerging markets tend to have different volatility characteristics.

The study is consistent with the general behavior of emerging markets. Joo & Ghulam (2023) reported the presence of volatility persistence and leverage effects in Brazil, India, Africa, and other emerging markets. Shamiri & Hassan (2007) reported that asymmetric models performed better than their symmetric counterparts in Malaysia and Singapore stock exchanges. Kayral et al. (2020) reported leverage effects in Brazil, China, Mexico, Turkey, and other emerging markets. Ezzat (2020) reported that EGARCH performed better in capturing leverage effects during political turmoil in Egypt.

5. Conclusion

The study aims to investigate the dynamics of volatility for the Nepal Stock Exchange (NEPSE) stock prices based on the series of returns from August 15, 2014, up to April 30, 2024, employing symmetric and asymmetric GARCH models. This study began with an overview of the development of the Nepalese stock exchange market, which revealed that the stock exchange market has shown remarkable growth with the establishment of SEBON, the introduction of electronic trading, and dematerialization. Despite the remarkable development, the stock exchange market has been facing the challenge of fluctuations in stock prices, market capitalization, and trading volumes.

The findings revealed that the Nepalese stock exchange market has high volatility persistence, as the sum of the ARCH and GARCH coefficients was close to one for all the estimated models. This revealed that the impact of volatility shocks persists for a longer time, decaying slowly, which shows that the Nepalese stock exchange market is inefficient in processing information. GARCH-M (1,1) model findings revealed that the risk premium was positive and statistically insignificant, which shows that investors in Nepal do not receive any compensation for facing high risks, which contradicts the risk-return trade-off theory.

One of the key findings is the confirmation of leverage effects in the Nepalese market across all models of asymmetric GARCH. The TGARCH (1,1), EGARCH (1,1), and PGARCH (1,1) models consistently demonstrated that negative shocks affect the market more than positive shocks of equal magnitude. This phenomenon is consistent with Black's (1976) leverage effect theory and prospect theory (Kahneman and Tversky, 1979), which indicate that investors respond more to negative news due to loss aversion and increased uncertainty.

Among all models used in this analysis, the PGARCH (1,1) model was found to be the best fit to explain the conditional variance of the Nepalese stock market with the lowest AIC (-6.0392) and the highest log-likelihood (6701.468). The sum of ARCH and GARCH coefficients (0.9370) reveals high volatility persistence with effects decaying over 10.65 days. The results are consistent with the findings of previous studies by Thapa and Gautam (2016) from Nepal, Akhtar and Khan (2016) from Pakistan, Haniff and Pok (2014) from Malaysia, and Atoi (2014) from Nigeria.

In conclusion, the results obtained from the NEPSE index show the existence of significant asymmetry in volatility with persistent effects, which confirms the non-efficient functioning of the market. The leverage effect shows the existence of negative news, which results in high volatility. This is an indication that the current mechanisms need to be improved, along with the regulatory environment and the level of investor protection. It is recommended that the authorities need to improve the dissemination of information, promote institutional investors, and enhance the level of financial literacy in the economy. The results obtained by employing the PGARCH (1,1) model show the best model for volatility forecasting in the Nepalese stock market.

References

Akhtar, S., & Khan, N. U. (2016). Modeling volatility on the Karachi stock exchange, Pakistan. *Journal of Asia Business Studies, 10*(3), 253-275.

Alberg, D., Shalit, H., & Yosef, R. (2008). Estimating stock market volatility using asymmetric GARCH models. *Applied Financial Economics, 18(*15), 1201-1208.

Atoi, N. V. (2014). Testing volatility in Nigeria stock market using GARCH models. *CBN Journal of Applied Statistics (JAS), 5*(2), 4.

Bekaert, G., & Harvey, C. R. (1997). Emerging equity market volatility. *Journal of Financial Economics, 43*(1), 29-77.

Black, F. (1976). *Studies of stock price volatility changes*. Proceedings of the 1976 Meetings of the American Statistical Association, Business and Economic Statistics Section, 177–181.

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy, 81*, 637–654.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*, 307–327.

Bollerslev, T., Chou, Y. R., & Kroner, K. F. (1992). Arch modeling in finance: A review of the theory and empirical evidence. *Journal of Econometrics, 52*(1-2), 5–59.

Box, G. E. P., & Jenkins, G. M. (1970). Time series analysis, forecasting and control. Holden-Day.

Christie, A. A. (1982). The stochastic behavior of common stock variances: Value, leverage, and interest rate effects. *Journal of Financial Economics, 10*(4), 407-432.

Dangal, R. P., & Gajurel, R. P. (2021). Volatility of Daily Nepal Stock Exchange (NEPSE) Index Return: A GARCH Family Models. *Tribhuvan University Journal, 36(*01), 31-44.

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*(366a), 427-431.

Ding, Z., Granger, C. W., & Engle, R. F. (1993). A long-memory property of stock market returns and a new model. *Journal of Empirical Finance, 1*(1), 83-106.

Engle, R. F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of UK inflation. *Econometrica, 50,* 987-1008.

Engle, R. F., & Granger, C. W. (1987). Co-integration and error correction: Representation, estimation, and testing. Econometrica: *Journal of the Econometric Society, 251*-276.

Ezzat, H. (2020). The application of GARCH and EGARCH in modeling the volatility of daily stock returns during massive shocks*: The empirical case of Egypt, 143*-154.

Fama, E. F. (1970). Efficient capital markets. *Journal of Finance, 25*(2), 383-417.

G.C., S. B. (2008). Volatility analysis of Nepalese stock market. *Journal of Nepalese Business Studies, 5*(1), 76–84.

Gokcan, S. (2000). Forecasting volatility of emerging stock markets: Linear versus non-linear GARCH models*. Journal of Forecasting, 19*(6), 499–504.

Haniff, M. N., & Pok, W. C. (2010). Intraday volatility and periodicity in the Malaysian stock returns. *Research in International Business and Finance, 24*(3), 329-343.

Harvey, C. R. (1995). Predictable risk and returns in emerging markets. *The Review of Financial Studies, 8*(3), 773-816.

Joo, B. A., & Ghulam, Y. A. (2023). The predictability, volatility persistence, and leverage effects in stock market returns: A study of BRICS stock market indices. *American Journal of Finance and Accounting, 7*(3-4), 188-213.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47*(2), 263-291.

Kayral, I. E., Alagoz, H. M., & Tandogan, N. S. (2020). *The asymmetry effect and volatility persistence in stock market returns: Evidence from Brazil, China, Mexico, and Turkey*. In Emerging Market Finance: New Challenges and Opportunities (pp. 149-163). Emerald Publishing Limited.

Kothari, C. R. (2004). Research methodology: Methods and techniques. *New Age Publication*.

Mala, R., & Reddy, M. (2007). Measuring stock market volatility in emerging economy. *International Research Journal of Finance and Economics, 8*(1), 126-133.

Miller, M. (1991). Financial Innovation and Market Volatility. In Blackwell (Ed.), *Financial Innovation and Market Volatility* (pp. 20-25). Cambridge.

Mullins, G. E. (2000). Stock market volatility: Measures and results. Retrieved from http://www.uwsp.edu/.../Stock%20Market%20VolatilityMeasures%20and%20Results.pdf

Nelson, C. R., & Plosser, C. R. (1982). Trends and random walks in macroeconomic time series: some evidence and implications. *Journal of Monetary Economics, 10(*2), 139-162.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. Econometrica: *Journal of the Econometric Society, 347*-370.

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. Biometrika, 75(2), 335-346.

Poon, S. H., & Granger, C. W. J. (2003). Forecasting volatility in financial markets: A review. *Journal of Economic Literature, 41*(2), 478-539.

Porwal, H., & Gupta, R. (2006). The stock market volatility. *The Journal of Accounting and Finance, 20*(1), 31-44.

Rana, S. B. (2020). Dynamics of time-varying volatility in stock returns: Evidence from Nepal stock exchange. *Journal of Business and Social Sciences Research, 5*(1), 15-34.

Schwartz, R. A. (1989). Equity markets: Structure, trading, and performance. Harper & Row.

Schwert, G. W. (1989). Why does stock volatility change over time? *The Journal of Finance, 44*(5), 1115-53.

Shamiri, A., & Hassan, A. (2007). Modeling and forecasting volatility of the Malaysian and the Singaporean stock indices using asymmetric GARCH models and nonnormal densities. *Journal of Malaysian Mathematical Sciences, 1,* 83-102.

Sharma, S., Aggarwal, V., & Yadav, M. P. (2021). Comparison of linear and non-linear GARCH models for forecasting volatility of select emerging countries. *Journal of Advances in Management Research, 18*(4), 526-547.

Thapa, B. S. (2012). Stock market volatility in Nepal. *The Lumbini Journal of Business and Economics, 2*(1), 22-35.

Thapa, B. S., & Gautam, C. M. (2016). Stock return volatility and asymmetries in the stock market of Nepal. *The Nepalese Management Review.*

Vasudevan, R. D., & Vetrivel, S. C. (2016). Forecasting stock market volatility using GARCH models: Evidence from the Indian stock market. *Asian Journal of Research in Social Sciences and Humanities, 6*(8), 1565-1574.

Wang, P. (2009). Financial econometrics (2nd ed.). Routledge, Taylor & Francis Group.

Yu, J. (2002). Forecasting volatility in the New Zealand stock market. *Applied Financial Economics, 12*, 193-202.