MODELING VOLATILITY DYNAMICS OF THE NEPAL STOCK EXCHANGE INDEX: EVIDENCE FROM GARCH-FAMILY MODELS

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Abstract

This study examined the volatility dynamics of the Nepal Stock Exchange Index using GARCH-based frameworks on 1,103 daily observations from November 2020 to July 2025. The Bai–Perron structural break test showed a single regime. The GARCH(1,1) model revealed strong volatility persistence and clustering, whereas the EGARCH(1,1) model identified a clear leverage effect, showing that negative shocks amplify volatility more than positive shocks. The PARCH(1,1) model additionally captured nonlinear and asymmetric volatility behaviour, supported by a significant power term. Diagnostic tests validated that all models were correctly specified and free from residual autocorrelation. Among the estimated models, the PARCH(1,1) specification provided the best fit, revealed by a log-likelihood value of 4080.904 and an AIC of –7.3955. The overall findings revealed that NEPSE returns exhibit persistent, clustered, asymmetric, and nonlinear volatility patterns, and the PARCH(1,1) model most effectively captured all these dynamics, offering practical implications for investors and policymakers.

Keywords: *NEPSE, GARCH, EGARCH, PARCH, volatility dynamics, leverage effect.*

Introduction

Volatility in the stock return represents the level of risk and uncertainties related to the asset returns. Understanding volatility dynamics is important, particularly in emerging countries where market structures are changing and information asymmetries are common. Time-varying volatility in stock returns has been the focus of extensive study using frameworks featuring Engle's (1982) ARCH and followed by Bollerslev's (1986) GARCH with GARCH selected for its simple estimates. Extensions that handle asymmetric volatility and leverage affects incorporate GARCH-M, E-GARCH, and T-GARCH (Nelson, 1991; Glosten, Jagannathan, & Runkle, 1993). Evidence from the Indian stock market using the BSE 500 index establishes that the GARCH(1,1) framework is known for featuring volatility clustering, fat tails, and mean reversion adequately capturing these features (Goudarzi & Ramanarayanan, 2011).

Nepal Stock Exchange (NEPSE), Nepal's key stock market, has grown significantly over the last two decades; however, empirical studies on stock market volatility are still insufficient. In Nepal, research of NEPSE returns reveals constant volatility (G.C., 2008; Gaire, 2017), and thus Rana (2020) supports that results, however, indicates no noteworthy leverage impact. This study tries to make a clearer understanding of market behavior of Nepalese stock market, including short-term shocks and volatility clustering, and aims to fill this gap by modeling the daily volatility of NEPSE returns, GARCH(1,1), EGARCH(1,1), as well as PARCH(1,1) frameworks are applied to capture both shock persistence and potential asymmetry in reaction to positive and negative returns. By analyzing 1,103 daily observations, this study gives a comprehensive insight into how the Nepalese stock market is risky, offering practical implications for market participants and will provide a significant contribution to the literature on volatility in emerging markets.

The Nepal Stock Exchange (NEPSE)'s volatility has been studied extensively by using various econometric methods, including GARCH-family and related models. These studies have provided valuable insights into market dynamics; risk behaviour present in the stock market and their mitigation. However, the nature of financial markets necessitates continuous documentation. Market structures, investor profiles, and policy environments change over time, and the risk landscape reflected in price movements changes with the change of time and situation. This study addresses this need by applying GARCH-family techniques to a recent set of daily observations, extending and reinforcing the historical record. The analysis is situated within the same methodological framework, ensuring fresh results with the new challenges established in the new timeframe. This research adds a valuable insight into the current situation to the stock market behaviour providing an updated perspective on volatility patterns and precision understanding enabling future scholars, investors, and policymakers to base their decisions and analyses as the NEPSE continues to evolve.

Statement of the Problem

Volatility has been studied extensively by using various econometric approaches to assess market dynamics; risk behaviour present in the stock market and their mitigation. However, the nature of financial markets necessitates continuous documentation. Market structures, investor profiles, and policy environments change over time, and the risk landscape reflected in price movements changes with situation. Such needs are addressed by applying GARCH-type models with a recent set of daily observations, extending and reinforcing the historical record by the analysis within the same methodological framework, ensuring fresh results to cope up new challenges developed in the new timeframe in the market providing an updated perspective on volatility patterns and precision understanding enabling future scholars, investors, and policymakers to base their decisions and analyses as the NEPSE continues to evolve.

Research Questions

Stock market volatility is associated with the degree of risks and uncertainties in the asset returns and that shifts rapidly due to structural shifts and limited market depths and the informational insufficiencies, particularly in emerging stock markets. Despite the application of GARCH-type models in the past, this study surpasses all the past empirical research messages, especially to address the post-2020 scenario, by conveying the updated and deeper volatility assessments adopting advanced conditional volatility models. GARCH-type models are applied here to capture volatility clustering, asymmetric shock responses, and nonlinear dynamics common in small and emerging markets and assist in determining whether modern volatility behaviour tracks the patterns previously reported or if new risks have emerged. Based on such backgrounds, the following research questions are set to address the existing empirical gaps.

1. To what extent does the NEPSE exhibit persistent and regime-dependent volatility clustering when analysed with the GARCH-family models?
2. How asymmetrically do the positive and negative shocks affect NEPSE volatility, and to what degree does leverage influence recent market behaviour?
3. Which of the GARCH-family specifications (GARCH, EGARCH, or PARCH) most accurately captures NEPSE's volatility, and what are the implications for risk forecasting and market stability?

Objectives of the Study

The following goals are framed for comprehending current market risk dynamics by using well-established GARCH-family models:

1. To examine the presence and nonlinear persistence of volatility clustering in daily NEPSE returns by applying the frameworks of GARCH(1,1), EGARCH(1,1), as well as PARCH(1,1) frameworks.
2. To analyse the asymmetric responses of volatility to positive and negative market shocks, capturing the potential leverage and nonlinear effects in the Nepalese stock market.
3. To provide updated empirical evidence on the current risk dynamics of NEPSE and to offer insights supporting informed decision-making for investors, policymakers, and future researchers.

Literature Review

In recent periods, econometric models, especially the ARCH/GARCH family, have been highly employed to analyse the volatility dynamics. Engle's (1982) Autoregressive Conditional Heteroskedasticity (ARCH) model assumes that current variance gets affected by previous error terms. Bollerslev (1986) expanded on this to create the Generalized ARCH (GARCH) framework that captures persistence, volatility clustering, and many other related facts that are ubiquitous in stock markets. Similarly, Nelson (1991) proposed the Exponential GARCH (EGARCH) framework for asymmetries to explain why negative shocks elevate volatility compared to positive shocks. Glosten et al. (1993) improved the PARCH framework by taking nonlinear and flexible volatility responses into account. According to studies by Pagan and Schwert (1990) and Episcopos (1996), GARCH-type models are able in predicting the phenomenon of shock persistence and volatility clustering. Alberola (2007), Kaur (2004), Bekaert and Wu (2000), and Basher et al. (2007), were among the latter research that found that clustering and asymmetry are usual features in stock returns. Boako et al. (2015), Hasan and Hady (2014), Banumathy and Azhagaiah (2015), and Alam et al. (2013) are other additional studies that have supported how well symmetric and asymmetric GARCH frameworks work specifications in simulating leverage effects and persistent volatility.

Though the effects of volatility vary for every market, Karmakar (2007) showed that Indian stock market time-varying and high persistent, volatility reacts highly to negative shocks although expected returns are not substantially influenced by risk. Such leverage impacts were further supported by Aliyev et al. (2020) showing that Nasdaq 100 volatility shocks were asymmetric and long-lasting. Other studies, including Goudarzi and Ramanarayanan (2011), Lim and Sek (2013), Ugurlu et al. (2014), and Roni et al. (2017) all indicated that asymmetry, volatility clustering, and persistence are more applicable to emerging markets in Asia, Europe, and Africa rather than in developed economies. Return connectivity across JSE size-based indexes varies over time and relies on regime, based on Lawrence et al. (2024). These shifts were guided by the macroeconomic variables, and COVID-19 magnifies the co-movements with each other.

Taking data from January 1993 to May 2021, Gupta (2023) studied the case of G4 countries' emerging markets, assessing the 2008 worldwide economic downturn, the 2015 Russian crises, and the COVID-19 worldwide epidemic all contributed to volatility forecasting. employing the symmetrical frameworks GARCH, EGARCH, and GJR-GARCH, the study revealed that GARCH is the most effective way to construct asymmetric attractions to volatility and found the phenomenon of the greater impact of negative shocks on volatility. Kumar & Sharma (2024) conducted a volatility and return analysis from April 2008 to March 2024 on indices of ten public and seven private sector Indian banks in BSE by using the frameworks of GARCH, GARCH-M, as well as EGARCH and demonstrated that most of the indices had persistence of volatility, while the EGARCH model had the most success explaining asymmetric volatility and leverage shifting although the GARCH-M model showed that the risk premium was insignificant. This indicates that the additional risk assumed by the investors was not worth the payoff.

Chen et al. (2025) observed that decomposed trade volumes, which reveal private information flows, are important factors which contribute to volatility clustering and systemic risk in an international market. When analyzing the volatility of the Nepalese stock market, G.C. (2008) found that GARCH(1,1) could best describe persistent volatility and clustering, without any observable asymmetry. Thapa and Gautam (2016) analyzed volatility and asymmetries in the Nepalese stock market employing daily NEPSE index data points from July 1997 to December 2012. GARCH-type models resulted in high market volatility with significant clustering and asymmetric effects. The PGARCH(1,1) model demonstrated that stock returns respond to good and bad news in different ways. Additionally, the GARCH-M approach showed a lack of significant risk premiums, indicating weak compensation for greater risk. Gajurel (2019) adopted a GARCH- family framework and analyze NEPSE index data from 1995 to 2019 to figure out the asymmetric volatility in the Nepalese market along with the spillover influence from the Indian and U.S. markets. Opposing other studies across the world, the study showed an inverted asymmetric effect, implying that negative shocks caused less volatility than positive shocks. Further finding a negative spillover from the Indian market to Nepal, also noticed the presence of ineffective traders, implying that market manipulation strategies like "pump and dump" methods possessed an impact on volatility dynamics.

By GARCH-series models, Rana (2022) analyzed the volatility of NEPSE stock returns within the period of COVID-19 during March 2020 and February 2022. In the result, the GARCH (1,1) model showed persistent volatility, where the TGARCH(1,1) model suggested significant leverage effects, ensuring that positive shocks depicted a weaker effect on the stock than that of the negative ones. Dangal and Gajurel (2021) studied the NEPSE Index volatility behaviour by using both the symmetric as well as asymmetric GARCH techniques employing GARCH-series models and findings revealed strong volatility clustering and the presence of leverage effects which suggesting that Nepal's stock market has a persistent and asymmetric volatility patterns.

Hence, the study clearly supports the assumption that GARCH family models adequately represent the universal characteristics of stock markets, including volatility clustering, persistence, and leverage effects. Since it can provide insight into the dynamics of risk in a small, developing capital market like Nepal focusing after COVID-19 impact in Nepalese stock market, fulfilling this gap is essential for both academic research and policy, as it can shed light on risk dynamics in a small and developing capital market like Nepal.

Research Methods

Employing a quantitative research design with 1,103 daily time-series data from 2020 November to 2025 July, the volatility of daily returns in the Nepal Stock Exchange (NEPSE) is analyzed to assess the dynamic behaviour of market volatility, including persistence, clustering, along with the asymmetry effects. The data are log transformed. The general equation is designed to capture the volatility as:

$$\Delta Ln(NEPSE)_t = Ln(NEPSE_t) - Ln(NEPSE_{t-1}) \tag{1}$$

Econometric Models

To capture volatility dynamics, the study employs the following GARCH-family models.

GARCH(1,1) Specification

The basic GARCH(1,1) approach, which describes how volatility (variance) varies over time, depends on the variance equation below to capture volatility clustering and persistence.

$$\sigma_t^2 = C + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{2}$$

Here, the conditional variance (volatility) is denoted by σ_t^2 is at time t, C stands as constant term, and the squared error known by ε_{t-1}^2, as the from the previous period (measures past shocks). Likewise, α represents the coefficient for the impact of past shocks (how past surprises affect current volatility), σ_{t-1}^2 represents the previous period's variance, and β represents the coefficient for the persistence of volatility.

EGARCH(1,1) Model

This model incorporates asymmetry and leverage effects and enhances the accuracy of volatility modeling. To Capture such asymmetric Volatility reactions to both positive as well as negative shocks, logarithmic variance specification allows for leverage effects, the equation is designed as:

$$Log(\sigma_t^2) = C + \alpha \left(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}}\right) + \gamma \left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) + \beta Log(\sigma_{t-1}^2) \tag{3}$$

Here, α stands for the magnitude effect known as the size of past shocks, γ stands for leverage or asymmetry parameter, and β stands for persistence of volatility.

PARCH(1,1)

Power ARCH (PARCH) technique is in fact an upgraded form of basic GARCH model that integrates the power element in the conditional standard deviation, which offers additional flexibility in capturing volatility clustering and asymmetric shock effects. The PARCH (1,1) variation accounts for nonlinear and power effects in volatility. The general PARCH (1,1) specification is:

$$\sigma_t^{\delta} = C + \alpha\,(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^{\delta} + \beta\sigma_{t-1}^{\delta} \tag{4}$$

As in the above equations, here too, σ_t represents conditional standard deviation (volatility), *C* stands as a constant term, ε_{t-1} is the past shock (error), *α* measures the impact of past shocks, and *γ* measures leverage or asymmetric effect (negative shocks affect to the volatility differently than that of the positive shocks). Likewise, *β* measures the persistence of volatility, and *δ* is the power parameter, allowing nonlinear effects of shocks on volatility.

Discussion of Results

To establish reliable model conditions, the analysis commences with initial tests including stationarity, structural break detection, and lag order selection. Based on these results, GARCH-family models are estimated and then evaluated through diagnostic tests to ensure the overall fitness of the models.

Stationary Test

Time series data must be stationary to get non-spurious results. Stationarity implies that over time, the mean, variance, and autocovariance of a series remain constant. For this Augmented Dickey Fuller (ADF) test is conducted which gives whether the data are level stationary or first difference stationary. **Table 1** presents the results for the study.

Table 1

Stationarity Test (ADF)

Variable	Test Form	*t*-Statistic	*p*-Value	Result
	Constant	–1.5617	.5019	Non-stationary
At Level	Constant & Trend	–1.5518	.8111	Non-stationary
	None	0.6819	.8629	Non-stationary
	Constant	–17.5785	< .001	Stationary
At First Difference	Constant & Trend	–17.5716	< .001	Stationary
	None	–17.5687	< .001	Stationary

The Augmented Dickey–Fuller result states that the NEPSE index is non-stationary in its level form, as the *p*-values across all specifications ranged from .50 to .86, and all are well above the

5% significance threshold, and when the series is transformed into its first difference, the ADF t-statistic becomes highly negative approximately –17.6 with $p < .001$, confirming the data are strongly stationary in first difference. Hence, the result implies that NEPSE is integrated of order one, I(1), for all subsequent GARCH-family estimations to ensure stationary and valid statistical inference.

Structural Brakes and Regime shift

To examine potential structural changes and regime shifts in the NEPSE index, the Bai–Perron multiple breakpoint test is applied and examined presence of the structural breaks, and the regime shifts in the mean of the series at unknown points in time.

Table 2

Bai–Perron Multiple Breakpoint Test Results

Hypothesis Tested	Sequential *F*-Statistic	Scaled *F*-Statistic	5% Critical Value	Decision (5% level)
0 vs. 1 break	7.49	7.49	8.58	No structural break

Table 2 presents the sequential and scaled F-statistics for testing 0 versus 1 break is 7.49 for both are lower than the critical value 8.58 for the level of 5 % threshold which clearly states that there exists no significant structural breaks or regime shifts during the study period.

VAR Lag Order Selection Criteria

While modeling volatility of the NEPSE Index, to get a correct lag length is essential that can accurately capture the time-dependent dynamics. AIC, BIC, HQ, and the LR test are some common criteria that help to determine the optimal lag structure by balancing model fit and simplicity. **Table 3** presents the lag selection criteria for this study.

Table 3

VAR Lag Order Selection Technique

Lag	LogL	LR	FPE	AIC	SC	HQ
0	4005.18	NA	3.88e-05	–7.3202	–7.3157	–7.3185
1	4008.24	6.12	3.86e-05	–7.3240	–7.3149	–7.3206
2	4011.09	5.69	3.85e-05	–7.3274	–7.3137	–7.3222
3	4017.83	13.43*	3.81e-05*	–7.3379*	–7.3196*	–7.3310*
4	4017.86	0.07	3.81e-05	–7.3361	–7.3133	–7.3275

All major criteria in **Table 3** indicate that lag 3 is an optimal lag for this study that can capture the essential dynamics of the NEPSE series without overfitting as it can provide the best balance between accuracy and simplicity to analyse NEPSE.

GARCH-Family Model Estimation Results for NEPSE Volatility

To examine the volatility behavior of the NEPSE index, GARCH-family models are widely applied since these models can effectively capture persistence, asymmetry, and nonlinear effects in financial time series data. In this study, the GARCH(1,1), including the EGARCH(1,1), as well as the PARCH(1,1) econometric models used to provide an assessment of volatility clustering, leverage effects, and power dynamics in the Nepalese stock market.

Table 4

GARCH-Family Model Estimation Results

Model	Variable /Symbol	Coefficient	Std. Error	*z*-Statistic	*p*-Value	Significance
GARCH(1,1)	Mean (C)	0.000269	0.000179	1.499	.1339	–
	Constant (ω)	1.86E-06	4.98E-07	3.740	< .001	***
	ARCH term (α)	0.084314	0.015573	5.414	< .001	***
	GARCH term (β)	0.866451	0.024188	35.821	< .001	***
EGARCH(1,1)	Mean (C)	0.000104	0.000187	0.552	.5807	–
	Constant (ω)	-0.682599	0.146479	-4.660	< .001	***
	Magnitude effect (α)	0.185743	0.026820	6.926	< .001	***
	Leverage/Asymmetry (γ)	-0.041163	0.013676	-3.010	.0026	**
	Persistence (β)	0.947165	0.013323	71.094	< .001	***
PARCH(1,1)	Mean (C)	0.000143	0.000190	0.754	.4509	–
	Constant (ω)	2.76E-06	7.47E-06	0.370	.7117	–
	ARCH term (α)	0.088139	0.018820	4.683	< .001	***
	Leverage/Asymmetry (γ)	0.239098	0.060815	3.932	< .001	***
	GARCH term (β)	0.862426	0.025385	33.973	< .001	***
	Power effect (δ)	1.929868	0.528111	3.654	< .001	***

The estimation of GARCH-type models presented in **Table 4** provides an important insight into the volatility dynamics of the stock market of Nepal.

In the GARCH (1,1) model, mean equation coefficient ($C = 0.000269$, $p = .1339$) a positive and statistically insignificant value confirms that daily returns do not show a significant drift over time. The variance equation shows a constant term ($\omega = 1.86 \times 10$□□, $p < .001$), which is highly significant, signifying a baseline level of volatility in the NEPSE returns. The ARCH term ($\alpha = 0.0843$, $p < .001$) confirms that current volatility is significantly influenced by previous shocks, while the GARCH term ($\beta = 0.8665$, $p < .001$) is also highly significant, indicating a strong volatility persistence. Likewise, the sum of ARCH term and GARCH term ($\alpha + \beta = 0.9508$) suggests that shocks to NEPSE volatility are long-lasting and consistent and confirm the presence of volatility clustering in stock market of Nepal.

EGARCH (1,1) model, on the other hand integrates the leverage and asymmetry effects, provides further insights. The mean equation coefficient ($C = 0.000104$, $p = .5807$) states that, on average, the daily log returns of NEPSE do not have any systematic upward and downward drift in the sample period. The constant term ($\omega = -0.6826$, $p < .001$) is significant and negative value shows a lower base line log variance to NEPSE Returns. Similarly, the coefficient for the magnitude of shocks ($\alpha = 0.1857$, $p < .001$) confirms that the past shocks strongly influence the current volatility in the NEPSE Index. Likewise, the asymmetry term ($\gamma = -0.0412$, $p = .0026$) points the presence of a leverage effect, as negative shocks intensify the volatility higher than positive shocks of equal size. And the persistence parameter ($\beta = 0.9472$, $p < .001$) indicates that the long-lasting nature of volatility in NEPSE returns. Overall, it is established from the EGARCH results that the Nepalese stock market exhibits an asymmetric response to volatility and that volatility clustering continues to be significant.

The PARCH(1,1) model is used to determine the nonlinear and power effects in the GARCH family by providing complementary evidence. In this, the mean equation coefficient ($C = 0.000143$, $p = .4509$) is statistically insignificant and consistent with the previous models. The variance equation shows that the baseline variance ($\omega = 2.76 \times 10^{-6}$, $p = .712$) is insignificant. The ARCH coefficient ($\alpha = 0.0881$, $p < .001$) is statistically significant and states that the past shocks influence current volatility, while the asymmetric or leverage coefficient ($\gamma = 0.\ 2391$, $p < .001$) is positive and highly significant, confirm that the negative and positive shocks affect volatility in different ways. Likewise, the GARCH term ($\beta = 0.8624$, $p < .001$) demonstrates strong persistence of volatility, and the power parameter ($\delta = 1.9299$, $p <.001$) confirms the presence of nonlinear effects in volatility dynamics. Ultimately, volatility responds differently to shocks of various magnitudes, showing the complexity and nonlinearity of NEPSE returns, and all these confirm nonlinear, asymmetric, and volatility-persistent dynamics in NEPSE returns.

In conclusion, the mean equation coefficients of all the models are statistically in significant stating that the expected daily returns of NEPSE are nearly zero and that the volatility, rather than the mean returns, dominates the dynamics of the NEPSE Index while the variance equations continuously show a significant ARCH and GARCH or Persistence term, confirming the volatility clustering. Additionally, the EGARCH and PARCH models capture asymmetric and nonlinear effects showing leverage terms stating that the negative shocks generally show a bigger influence on the NEPSE Index volatility rather than that of the positive shocks. Likewise PARCH power term revealing that the volatility responses rise nonlinearly with shock size.

In a nutshell these findings suggest that NEPSE returns show persistent, clustered, asymmetric and nonlinearity which is very important to make informed and rational decisions. Hence, NEPSE volatility analysis from the study's framework reveals strong persistence, clustering, leverage, and nonlinear effects, with PARCH providing the best overall fit as compared to GARCH and EGARCH, providing valuable insights.

Model Fit and Diagnostic Tests

Table 5

Model Fit and Overall Diagnostic Statistics

Model	Log Likelihood	AIC	BIC	Durbin-Watson
GARCH (1,1)	4074.202	-7.3869	-7.3688	1.835
EGARCH (1,1)	4078.381	-7.3927	-7.3700	1.835
PARCH (1,1)	4080.904	-7.3955	-7.3682	1.836

Table 5 presents the model fit and the diagnostic statistics confirm that the PARCH(1,1) model fits NEPSE best, with the highest log-likelihood (4080.904) and lowest AIC (–7.3955) of the GARCH family outperforming over EGARCH and GARCH suggesting that PARCH is more capable of capturing the subtle dynamics in stock return volatility. Across all models, the Durbin-Watson statistics, around 1.835, signify that there are no serious autocorrelation issues in the residuals.

Residual Diagnostic Tests

The following residual diagnostic test are conducted for the test of goodness of fit of the models.

Ljung–Box Q-Test Results for GARCH, EGARCH, and PARCH Models

The Ljung-Box *Q*-statistics is a relevant residual diagnostic test regarding serial autocorrelation test that reveals the standardized residuals to serve GARCH-class models. The results reveal all the GARCH family models are free from significant autocorrelation, confirming proper model specification. The findings show that GARCH captures persistence, EGARCH adds leverage effects, and PARCH(1,1) incorporates both asymmetry and nonlinear dynamics. As per the superior log-likelihood and information criteria, rather than the GARCH(1,1) and EGARCH(1,1) models, the PARCH(1,1) model better explains market volatility in Nepal.

Jarque–Bera Normality Test

In the case of fitted volatility models, the Jarque-Bera normality test determines whether the standardized residuals follow a normal distribution.

Table 6

Normality Test Results by JB Statistics

No.	Model	*JB* Statistic	*p*-Value	Skewness	Kurtosis
1	GARCH(1,1)	190.98	< .001	0.58	4.68
2	EGARCH(1,1)	146.71	< .001	0.53	4.44
3	PARCH(1,1)	159.53	< .001	0.53	4.54

Table 6 presents the standardized residuals from GARCH-class models are assessed for normality by using histograms and the Jarque–Bera test. The *p*-values for all the GARCH-class models are < .001, indicating that normality is strongly rejected. The residuals show that they are positively skewed ranging from 0.53 to 0.58 and kurtosis ranging from 4.41 to 4.68, all are above the normal distribution value of 3 confirming their fat tails. Hence none of the models are fully capturing normality still EGARCH(1,1) shows a relatively lower Jarque–Bera statistic, implying a slightly better fit in terms of residual distribution. This result is consistent with volatility clustering and leptokurtosis as in stock return data, stressing the significance of using flexible models like EGARCH(1,1) and PARCH(1,1).

ARCH Test for Different GARCH Models

The ARCH test serves to find autoregressive conditional heteroscedasticity in time series data, and it is an important feature in financial return series. Addressing ARCH effects is essential for properly using GARCH models, which illustrate time-varying volatility and clustering in financial markets.

Table 7

ARCH Test Results for GARCH-Class Models

S. No.	Model	F-statistic	*p* (F-stat)	Obs.*R-squared	*p* (Chi-Square)
1	GARCH(1,1)	0.132	.9411	0.397	.9409
2	EGARCH(1,1)	0.172	.9157	0.516	.9153
3	PARCH(1,1)	0.117	.9502	0.352	.9500

Table 7 presents the ARCH test results based on the standardized residuals from the GARCH-class models. The F-statistics are 0.132 for GARCH(1,1), 0.172 for EGARCH(1,1), and 0.117 for PARCH(1,1), where the corresponding *p*-values for the F-test and Chi-square test range from .915 to .950, indicating that there is no significant ARCH effect in any model and that conditional heteroskedasticity has been captured adequately. Among the models, EGARCH(1,1) model shows a slightly higher Obs.*R-squared value of 0.516, but it remains insignificant, which suggests a comparable fit across all models. These findings clearly point out that GARCH-class models are appropriate for modelling volatility dynamics since there are no residual ARCH effects.

Summary of the diagnostic test results

Based on a set of diagnostic tests, the PARCH(1,1) model outperforms GARCH(1,1) and EGARCH(1,1) in capturing the volatility of stock returns, with the largest log-likelihood and lowest AIC for NEPSE. Residual diagnostics show that all the models do not have significant autocorrelation and ARCH effects, but none of them fully satisfy normality, with positive skewness and leptokurtosis present. Overall, PARCH(1,1) can effectively model the volatility dynamics including asymmetry and nonlinear effects and followed closely by EGARCH(1,1) and GARCH(1,1).

Conclusion and Recommendation

This study incorporated GARCH-class models to assess the volatility dynamics of NEPSE returns and established that returns are stationary at the first difference, with no structural breaks. The findings confirmed the strong volatility persistence across all models. In the GARCH (1,1) model, the ARCH term (α = 0.0843, p < .001) and the GARCH term (β = 0.8665, p < .001) revealed short-term and persistent volatility effects, and their sum ($\alpha + \beta$ = 0.9508) clearly stated a long-lasting volatility clustering. Similarly, the EGARCH (1,1) model provided further insights into asymmetric behavior, with a magnitude effect (α = 0.1857, p < .001), a leverage effect (γ = –0.0412, p = .0026), and a persistence parameter (β = 0.9472, p < .001). These results show that the negative shocks elevate the volatility more strongly than those of the positive shocks of the same size. The PARCH (1,1) model effectively captured asymmetry as well as nonlinear effects, as shown by the value of ARCH effect ($\alpha = 0.0881$, $p < .001$), asymmetric or leverage coefficient ($\gamma = 0.2391$, $p < .001$), GARCH term ($\beta = 0.8624$, $p < .001$), and the power parameter ($\delta = 1.9299$, $p < .001$). These results indicate that volatility responds disproportionately to large shocks, intensifying fluctuations, confirming nonlinear, persistent, and asymmetric volatility dynamics in NEPSE returns. Diagnostic tests confirmed that PARCH(1,1) best fit, with a log–likelihood of 4080.904 and an AIC of –7.3955, followed by EGARCH and then GARCH.

In conclusion, the NEPSE index establishes persistent, clustered, asymmetric, and nonlinear volatility. The PARCH(1,1) model explains these dynamics in the best way, while EGARCH captures leverage effects, and GARCH confirms persistence. The findings align with the prior studies showing that NEPSE returns exhibit clustered, asymmetry, and persistent volatility as shown by Karmakar (2007) and Thapa and Gautam (2016), however, the observed negative asymmetry differences with G.C. (2008) and Gajurel (2019) highlighting evolving volatility dynamics in Nepal's stock market. Based on the findings of this study, investors are advised to use PARCH(1,1) to manage the stock market risks, since this model accurately captured the volatility patterns of the Nepalese stock market. Policymakers are recommended to take precautions to address the Nepalese stock market's persistent volatility. Deeper information can be provided by using alternative techniques along with the larger datasets can be to make further study in the area.

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