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Macroeconomic Volatility Transmission and Shock Responses in the Nepalese Stock Market

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Abstract

This study examines the volatility properties of the Nepal Stock Exchange Index (NEPSE) using 223 monthly observations from July 2006 to January 2025. Based on EGARCH estimation, the Nepalese stock market demonstrates asymmetric, persistent, mean-reverting, and highly clustered volatility, with negative shocks causing larger movements than positive shocks of the same magnitude. Among the macroeconomic variables, only the treasury bill rate has a significant impact on stock returns, confirming that rising short-term interest rates reduce market performance. Variance decomposition establishes that NEPSE is largely self-driven in the short run, with its own innovations, accounting for approximately 95% of forecast error variance. Money supply exerts a small positive effect, and inflation has a minimal negative impact, while the contribution of TBR increases steadily over the medium and long term. IRF results suggest that NEPSE strongly responds to its own shocks in the initial periods, which gradually diminish over time as external macroeconomic variables influence the market. Findings reveal that internal market dynamics mainly drive short-term fluctuations, while the influence of rising interest rates strongly influence medium- and long-term behaviour. The NEPSE remains largely self-correcting in the short term, emphasizing the importance of stable monetary policy and effective macroeconomic management for market stability, growth, and development.

***Key Words**:* NEPSE, EGARCH model, volatility dynamics, VDC, IRF.

Introduction

The financial state of a country is reflected in the stock market, which funnels investments towards profitable undertakings. The NEPSE is essential for capital mobilization in Nepal; however, it is highly unpredictable and vulnerable to macroeconomic shocks. Market volatility is increased by inconsistent policies and traditional economic barriers. Knowing and evaluating this volatility is thus significant for investors and policymakers to make informed decisions and optimize returns. Volatility is the variation in the price of financial assets across different periods which is primarily determined by the deviation of returns. Volatility in the stock market is generally considered a risk factor for investment; however, if it can be analyzed properly, it can provide better profits as well. It shows the extent to which an asset's price deviates from its normal value, providing a crucial understanding of its risk profile. High volatility specifies larger price swings with greater uncertainty and while low volatility states more stable prices with a lower risk. Understanding volatility is essential for investors since it provides trading strategies and risk assessment by helping anticipate potential price movements and align investment decisions with risk tolerance.

Volatility modelling is very important to understand the stock market risk and to make informed decisions, particularly in emerging markets like Nepal. It is quite crucial for understanding financial issues in emerging markets where data limitations and market inefficiencies persist (Engle, 1982; Bollerslev, 1986). Stock market volatility influences investing decisions as it reflects the dynamic linkage between risk and return (Markowitz, 1952; Sharpe, 1964). The GARCH models are particularly used to analyze volatility; however, they sometimes fail to capture asymmetric effects where negative and positive shocks impact volatility in different ways (Nelson, 1991).

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This study employs the EGARCH model to address volatility asymmetry in the Nepalese stock market along with Impulse Response Functions (IRF) and Variance Decomposition (VDC) to investigate the dynamic transmission of shocks across macroeconomic variables and the stock index over time, allowing for the assessment of both the relative influence of each indicator to forecast error variances and the reactions over time after a shock occurs in the stock index (Sims, 1980; Lütkepohl, 2005). Since stock market volatility does not remain constant over time, it continuously fluctuates (Engle, 1982). Such fluctuations often cluster together, indicating that stock returns are not completely random (Mandelbrot, 1963).

This study tries to diagnose Nepalese stock market volatility by addressing a methodological gap in previous studies while allowing investors to assess their investment decisions. Classical econometric methods are focused on static causal relationships and often fail to capture dynamic market responses and volatility transmission. This study adopts the EGARCH model, VDC, and IRF techniques to analyze stock market volatility and the transmission of macroeconomic shocks over time.

Statement of the Problem

Despite the voluminous transactions and market activities in recent periods, the market continues to exhibit excessive volatility and uncertainty, which makes it difficult for investors, analysts and policymakers to interpret and forecast the market movement, especially during the periods of macroeconomic turbulence. Traditional regression and descriptive based approaches mostly laid a useful foundation for understanding market behaviour with partial and often inconsistent conclusions; however, to address dynamic and time-varying scenarios, advanced econometric models offer greater explanatory power. Hence, many fundamental research gaps remain unresolved, and some are listed as:

1. Despite the consistent and unpredictable volatility, limited information has been revealed regarding the short-term dynamics and asymmetric behaviour of the Nepal Stock Exchange.
2. The enduring consequences of essential macroeconomic drivers on the Nepalese stock market are not well-established.
3. The long-term impacts of macroeconomic indicator shocks on stock market performance are yet to be thoroughly evaluated.

Many prior studies are missing the consideration of the persistence and asymmetry of volatility, which are critical features for effective risk management and policy formulation. This omission weakens investor confidence and hinders the development of Nepal's capital market. This study aims to model and quantify the dynamic and time-varying impact of key macroeconomic elements on the NEPSE Index and its volatility. By employing EGARCH, Impulse Response Function Analysis as well as Variance Decomposition Analysis, this study seeks to establish a strong analytical framework for understanding Nepalese stock market behaviour, enhancing the confidence of investors and supporting policymaking.

Research Questions

Volatility in the stock index is a crucial factor in emerging markets that seriously impacts investment, financial decisions, and the economic development of the country. As the Nepalese stock market is very sensitive to the macroeconomic conditions leading to volatility clustering and high fluctuations in the stock price, it is very important to understand the volatility driving factors to build the confidence of the investors and market participants as

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well as policy effectiveness. Since traditional linear models cannot fully capture asymmetric volatility patterns, the advanced econometric framework EGARCH is used to measure volatility persistence and leverage effects, and the Impulse Response Function and Variance Decomposition provide the dynamic impact and relative contribution of macroeconomic shocks on the NEPSE Index, forming the following research questions.

1. How persistent and asymmetric is the volatility of the Nepal Stock Exchange over time?
2. How do the selected macroeconomic variables affect the volatility of the NEPSE Index?
3. How do shocks from macroeconomic variables and the stock market itself transmit and influence NEPSE volatility in the short run and long run?
4. Which macroeconomic variables contribute most to the forecast error variance of NEPSE, indicating their relative importance in stock market volatility?

Objectives of the Study

This study aims to empirically examine the dynamic link of selected variables with the volatility behaviour of the Nepal Stock Exchange (NEPSE). Hence, the following objectives are set up for this study.

1. To assess the asymmetry, persistent volatility, and short-term trends of the Nepal Stock Market.
2. To analyze the long-run impact of macroeconomic factors on stock market volatility.
3. To evaluate the impacts of macroeconomic shocks on the stock market performance over time.
4. To offer evidence-based recommendations to investors and policymakers for growth and expansion of the Nepalese stock market.

Literature Review

Stock market volatility has a significant role in making investment decisions and directly influences the behaviour of both the enterprises and individual investors. Many studies have shown that monetary aggregates and liquidity conditions significantly impact stock market volatility, particularly during economic uncertainty, emphasizing the importance of these variables in stock market forecasting. Fama (1981) established that changes in macroeconomic factors, particularly inflation and interest rates, significantly influence stock returns, signifying that investors regulate their expectations based on the existing economic environment. Chen, Roll, and Ross (1986) carried out further analysis by adding several macroeconomic indicators, covering industrial production, inflation, and interest rates, and showed that there exist immediate as well as enduring impacts on stock prices, supporting the fact that stock markets do not operate in isolation from the broader economy. Likewise, Worthington and Higgs (2004) gave empirical evidence from developed and emerging markets, confirming that variations in macroeconomic variables are replicated in stock market volatility, stressing the sensitivity of capital markets to economic fluctuations.

Empirical examination of the time-varying risk-return links in Bangladesh by Basher et al. (2007) found that the conditional volatility was significantly related to stock returns and that the parameter of the risk-return was quite sensitive to sample selection and data frequency, with a negative and statistically significant coefficient. GC (2008) studied 1,297 daily NEPSE returns data from 2003 to 2009 and found significant support with substantial persistence in conditional variance, time-varying volatility, and volatility clustering. Although asymmetric properties were not found, the GARCH(1,1) framework was found to be the ideal technique for forecasting, and NEPSE returns were leptokurtic, non-normal, and showed a significant time dependency. Zhang (2010) investigated the link between the U.S. market's volatility and high-frequency trading. A positive correlation persisted even after adjustment for the firms' external and fundamental factors, indicating the ability of complicated volatility models like EGARCH to capture the impacts of current trading mechanisms.

The autoregressive, moving average, and seasonal components that are crucial to the daily NEPSE index were highlighted by Gaire (2017), who employed the EGARCH model to test the volatility that came from both positive and negative shocks using daily NEPSE data from 2012 to 2015. In conclusion, the results revealed that NEPSE presents consistent, time-varying volatility driven by market dynamics, shocks, and structural events, and that suitable GARCH-based models provide insightful perspectives for investors and policymakers in managing market risk. Taking 2059 daily data from NEPSE Index from 2011 to 2020, Rana (2020) analyzed stock returns volatility using GARCH Models including those designed to capture asymmetric effects and the study found persistent volatility in daily returns, although the asymmetric models did not detect leverage effects and the GARCH-M model showed no significant risk premium. The GARCH(1,1) framework, together with the student's distribution accurately represented the volatility persistence, allowing investors to better manage risk in Nepal's stock market. Hamal and Gautam (2021) examined how the COVID-19 pandemic affected market return and volatility. The study found that due to the COVID-19 lockdown implemented by the government adversely affected market performance initially; however, the monetary policy restored confidence, while fiscal measures had a minor impact. The study stressed that clearer government actions and reliable information were vital factors to stabilize markets during crises. Dangal and Gajurel (2021) used asymmetric (TGARCH, EGARCH, PGARCH) and symmetric (GARCH(1,1); GARCH-M(1,1)) frameworks to analyze 3,392 daily NEPSE returns from June 1, 2006, to April 7, 2021. They discovered leverage effects and volatility clustering, with symmetric models better fitting the entire period and asymmetric models better suited for the pre- and post-earthquake periods

The impact of macroeconomic factors on Indian stock returns was analyzed by Mukhopadhyay and Sarkar (2003) who found that inflation, money supply growth, foreign market activity, and FDI significantly shaped stock market volatility, particularly after economic liberalization. By using the EGARCH model, Erdem et al. (2005) analyzed the stock market volatility in the Istanbul Stock Exchange and demonstrated that volatility in inflation and interest rates created unidirectional spillover effects, reinforcing their central role in driving stock market fluctuations. In the Nairobi Securities Exchange (NSE), Kirui et al. (2014) evaluated NSE volatility by employing TGARCH and Engle-Granger methods. The study found that a 1% currency depreciation reduced stock returns by 1.4%, while other macroeconomic factors exhibited limited or no significant impact.

Two common approaches, Impulse Response Functions (IRF) and Variance Decomposition (VDC) under Vector Autoregressive (VAR) models, are deployed to analyze the dynamic relationships of time series data to understand how, over time, shocks of one variable affect others (Sims, 1980; Lütkepohl, 2005). Under the VAR system, the Impulse Response Function helps to find the impact that a single shock possesses on both the present and the future values of all variables by providing insights into how one variable reacts over time after a shock happens in another variable. Likewise, Variance Decomposition is used to measure how shocks to one variable affect the current and future values of other variables. It describes the proportion of the forecast error variance of a variable that is attributable to shocks in other variables, thereby determining their relative importance or influence. Based on these methods to quantify connectedness and spillover effects across financial markets, allowing analysts to detect which markets or sectors are net transmitters or receivers of shocks. Similarly, Kilian (1998) mentioned the importance of these techniques to policymakers to assess the immediate as well as enduring impacts of economic fluctuations to address the systemic risks. Together, VDC and IRF provide a comprehensive framework for understanding interdependence, shock transmission, and index volatility in both financial and macroeconomic systems.

Research Methods

This study adopts strong econometric methods to assess how the Index of Nepal Stock Exchange performs in connection with the key macroeconomic variables. This ensures rigorous data collection, processing, and analysis, providing reliable, valid, and interpretable results for investors and policymakers. It employs a quantitative research design, focusing on causal relationships between macroeconomic indicators and stock market volatility using time series econometrics 223 secondary monthly time series data of Nepal Stock Exchange Index (NEPSE Index), broad money supply (MS), 91-day treasury bill rate (TBR), and consumer price index (CPI), from July 2006 to Jan 2025 are taken from the websites of Nepal Stock Exchange and Nepal Rastra Bank. All variables are transformed into natural logarithms.

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Model Specification

To address some limitations in volatility modeling particularly in financial time series data, Nelson (1991) introduced the EGARCH model as an improved version over traditional GARCH models (Bollerslev, 1986). It is commonly used to depict time-varying volatility (heteroskedasticity) in asset returns to capture volatility clustering and leverage effects.

Variability clustering is a common pattern in time series such as stock returns, for periods with elevated volatility followed by higher volatility and periods of lower volatility followed by lower volatility. Leverage effects are also evident in these series, demonstrating that market declines, or negative shocks typically cause greater volatility compared to positive shocks of equal amounts. The asymmetry in the way volatility reacts to positive against negative shocks is not well captured by traditional GARCH models, despite their ability to handle volatility clustering. It assures the conditional variance keeps positive without requiring non-negativity constraints on the parameters and allows an asymmetric impact. The EGARCH framework is more appropriate for financial return series that possess robust distributions, leverage effects, and volatility persistence, as it provides a linear form of the conditional variance. This approach helps analysts to get more accurate knowledge of time-varying uncertainties in financial markets by assisting them to examine the effects of past shocks' both direction and magnitude on current volatility. Below shows the mean equation of EGARH in equation (1) and the variance equation is in equation (2).

Mean equation

The first stage measures the effect of macroeconomic changes on NEPSE returns, where Let Y_t denotes the NEPSE returns at time t, defined as the first difference of ln($NEPSE_t$). The conditional mean in equation 1 is designed as:

$$Y_t = \beta_0 + \beta_1 \Delta MS_t + \beta_2 \Delta CPI_t + \beta_3 TBR_t + \varepsilon_t \quad (1)$$

where ΔMS_t and ΔCPI_t are the first difference of money supply, the first difference of consumer price index at time t, respectively, and TBR_t is the 91-day treasury bills rate in the level form at time t. Similarly, ε_t stands as the error term (innovation) that captures unexplained shocks in NEPSE returns from the mean equation. The coefficient β_0 is the intercept, while β_1, β_2, and β_3 measure the sensitivities of NEPSE returns to changes in money supply, consumer price index, and the treasury bill rate, respectively.

Variance Equation

To capture asymmetrical and leverage effects in volatility, the variance equation in equation 2 is designed as:

$$log(\sigma_t^2) = \omega + \beta\, log(\sigma_{\{t-1\}}^2) + \gamma \left(\frac{\varepsilon_{\{t-1\}}}{\sigma_{\{t-1\}}}\right) + \theta \left(\left|\frac{\varepsilon_{\{t-1\}}}{\sigma_{\{t-1\}}}\right| - \sqrt{\frac{2}{\pi}} \right) \quad (2)$$

Where, σ_t^2 stands as the conditional variance of innovation(error) ε_t at time t, likewise ω stands as the constant term (intercept) capturing the long-run average level of log variance, $\varepsilon_{\{t-1\}}$ represents innovation (residual) from the mean equation at time t-1, $\sigma_{\{t-1\}}$ represents Conditional standard deviation at time t-1, γ is the leverage (asymmetric) parameter. $\gamma \left(\frac{\varepsilon_{\{t-1\}}}{\sigma_{\{t-1\}}}\right)$ represents leverage or sign effect, and $\theta \left(\left|\frac{\varepsilon_{\{t-1\}}}{\sigma_{\{t-1\}}}\right| - \sqrt{\frac{2}{\pi}} \right)$ magnitude effect of shocks on volatility. θ represents the coefficient capturing the sensitivity of volatility to the magnitude of shocks. $\sqrt{\frac{2}{\pi}}$ is the expected value of the absolute value of a standard normal variable, used to standardize the magnitude effect.

Empirical Result and Discussion

The Nepal Stock Exchange (NEPSE) reflects the performance and stability of the Nepalese financial market and is influenced by both internal market dynamics and key macroeconomic variables. The analysis of these interactions' sheds light on the causes of stock market fluctuations along with the implications for investors and policymakers. Before analyzing these interactions, the collected time series data is checked based on the Unit Root Test for its stationarity to perform EGARCH, VDC, and IRF. VAR is also applied to lag selection criteria. Some diagnostic and stability tests for the model's stability, goodness of fit, and dependability are to be conducted in the subsequent stages.

Unit Root Test

Unit Root tests are performed to verify that the data collected is stationary. The Phillips – Perron and Augmented Dickey–Fuller tests are used to ensure that the data are stationary at the level or in the form of first difference. **Table 1** shows the results of ADF and PP. First, all data are transformed into natural logarithms. Equation 3 shows the specification for the ADF and PP tests:

$$Y_t = \beta_0 + \beta_1 \Delta MS_t + \beta_2 \Delta CPI_t + \beta_3 TBR_t + \varepsilon_t \quad (3)$$

Here, Δ indicates the first difference operator to transform non-stationary variables into a stationary form and ε_t is the error term.

Table 1

Phillips–Perron and Augmented Dickey–Fuller Tests

Variable	Level (PP)	Level (ADF)	First Difference (PP)	First Difference (ADF)	Result
LnNEPSE	$t = -0.921$ $p = .7804$	$t = -1.083$ $p = .7226$	$t = -12.263$ $p < .001$	$t = -12.161$ $p < .001$	I (1)
LnMS	$t = -2.519$ $p = .1123$	$t = -3.290$ $p = .0166$	$t = -17.545$ $p < .001$	$t = -3.041$ $p = .033$	I (1)

LnCPI	$t = -2.723$ $p = .0717$	$t = -2.488$ $p = .1198$	$t = -15.651$ $p < .001$	$t = -15.722$ $p < .001$	I (1)
LnTBR	$t = -3.905$ $p < .001$	$t = -3.002$ $p = .0363$	$t = -16.508$ $p < .001$	$t = -14.890$ $p < .001$	I (0)

Table 1 presents the log-transformed NEPSE (Y), consumer price index (CPI), broad money supply (MS), and treasury bill rate (TBR) examined at the 5% significance level. Outcomes show that NEPSE, MS, and CPI are non-stationary at the level; however, they become stationary at first difference, i.e., at first order I(1). TBR, however, is stationary in level I(0). Both PP and ADF tests gave consistent findings, so subsequent analyses employ first-difference data for NEPSE returns, money supply, and consumer price index and level data for treasury bill rate.

Selection of Lag Length Using the VAR Model

An appropriate lag selection is essential to capture data dynamics by avoiding overfitting or misspecification and for accurate estimation of the model by deploying the common criteria of the Schwarz Information Criteria (SIC), Hannan-Quinn Information Criteria (HQIC), or Akaike Information Criterion (AIC) in a VAR model. These criteria are evaluated within a maximum lag limit to determine the ideal lag for further analysis.

Table 2

Selecting lags with VAR

Lag	LogL	LR	FPE	AIC	SC	HQ	Selected Lag
0	1311.152	NA	5.82×10^{-11}	–12.21638	–12.15346	–12.19095	–
1	1473.975	318.038	1.47×10^{-11}	–13.58856	–13.27398*	–13.46144*	1
2	1488.595	28.010	1.49×10^{-11}	–13.57565	–13.00942	–13.34684	–
3	1510.726	41.572	1.41×10^{-11}*	–13.63295*	–12.81505	–13.30244	–

VAR result for lag length has shown two different results as per **Table 2**. Based on AIC and FPE lag, three is optimal whereas SC and HQ show one lag is optimal. To avoid overfitting or misspecification and for an accurate estimation of the model, based on SIC and HQIC, lag 1 is selected for this study.

EGARCH Analysis

To capture time-varying volatility and asymmetric responses of the NEPSE returns to shocks in macroeconomic variables, the EGARCH technique is employed. By providing a robust framework for analyzing market risk and return dynamics, it effectively identifies volatility

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clustering, persistence, and leverage effects. The EGARCH analysis result is presented in the following **Table 3**.

Table 3

Results of EGARCH(1,1) Estimation for ΔlnNEPSE

Model	Variable / Symbol	Estimated Coefficient	Standard Error	Z-Statistic	p-Value
EGARCH(1,1)	Mean Equation (*C*)	0.008024	0.002310	3.473	< .001
	ΔlnMS	0.121820	0.256697	0.475	.635
	ΔlnCPI	0.033941	0.026269	1.292	.196
	lnTBR	–0.017646	0.002061	–8.563	< .001
Variance Equation	ω (Constant)	–0.485462	0.040550	–11.972	< .001
	α (ARCH term)	–0.231642	0.051565	–4.492	< .001
	γ (Leverage / Asymmetry)	0.181243	0.033950	5.339	< .001
	β (GARCH / Persistence)	0.904985	0.000241	3754.0	< .001

Model Fit and Diagnostic Statistics

Statistic	Value	Statistic	Value
R^2	0.063	Mean Dependent VAR	0.004
Adjusted R^2	0.050	S.D. Dependent VAR	0.031
S.E. of Regression	0.031	Akaike Info Criterion	– 4.191
Sum Squared Resid	0.204	Schwarz Criterion	–4.068
Log Likelihood	473.186	Hannan-Quinn Criterion	–4.141
Durbin–Watson statistic	1.721		

Mean Equation

The mean equation of the EGARCH presented in **Table 3** illustrates how the NEPSE Index reacts to macroeconomic changes. Money supply possesses a coefficient of 0.1218 (p = .635) and coefficient of CPI 0.0339 (p = .196) show that they both are statistically insignificant at a 5 % level of significance. However, the treasury bill rate (TBR) along with a coefficient of –0.0176 (p < .001), possesses statistical significance stating that indicating that rising short-term interest rates of 1 % reduce the NEPSE Index by about 0.017 %. The coefficient of the constant term (*C)* is 0.008 (p < .001) states that it captures a small positive average growth when other variables are held constant.

Variance Equation part of EGARCH

The variance specification captures time-varying volatility. The magnitude of the constant term (ω = –0.4855, p < .001) represents the long-run mean of the logarithmic conditional variance and indicates the volatility of the market tends to revert toward the long-run level over time. The ARCH term (α = –0.2316, p < .001) captures short-term response to new shocks while the leverage coefficient (γ = 0.1812, p < .001) represents the asymmetry

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indicating that negative shocks increase volatility more than positive shocks of the same magnitude. Further, the leverage coefficient (γ = 0.1812, p < .001) confirms this asymmetry, indicating that negative shocks raise market volatility by about 18% relative to positive shocks, demonstrating a significant leverage effect. Likewise, the persistence parameter (β = 0.9050, p < .001) is very close to one, indicating a high degree of volatility persistence and confirms that shocks to volatility fade over time with about 9.5% (1– β) of any deviation from the long-run variance being corrected each period stating a strong and stable mean–reverting process in the volatility behaviour. Hence, the result shows that among the selected variables, only TBR is significant, and besides this, market volatility is highly persistent and asymmetric, with negative shocks more powerful than positive shocks of the same size.

Model Fit and Diagnostics Test Result

The values of R^2 = .063 and adjusted R^2 = .050 show a low explanatory power, which is typical for return models where volatility dynamics matter more than mean prediction. The standard error of regression (0.031) and the sum of squared residuals (.204) indicate a modest degree of residual variation. Likewise, information criteria AIC = –4.19, Schwarz = –4.07, Hannan–Quinn = –4.14 are negative and low, supporting the adequacy of the model. The log likelihood is 473.19, a strong indication of good likelihood fit, and the 1.72 Durbin–Watson statistic states that there is no serious autocorrelation in the residuals.

EGARCH Model Diagnostics

To confirm whether the EGARCH approach is well specified as well as reliable or not, key diagnostics, including the stability tests, are performed. These tests verify that the estimated volatility model is stable and free from misspecification and provide confidence that the EGARCH results are robust as well as trustworthy.

Heteroskedasticity ARCH-LM Test

This is an important diagnostic test, introduced by Robert Engle in 1982 for GARCH models to determine whether or not ARCH effects are present in the residuals. It is confirmed that the volatility structure has not been precisely captured with the presence of ARCH effects, and the model is not correctly specified; and their absence confirms correct specification.

Table 4

Heteroskedasticity: ARCH-LM Test

Statistic	Value	df	*p*

F-Statistic	0.003484	(1, 219)	.9530
Obs. * R-squared	0.003516	**(1)**	.9527

The ARCH test checks whether the residual variance changes over time. As shown in Table 4, both *p*- values (.9530 and .9527*)* are far above .05 significance level, indicating that the null hypothesis of no ARCH effect cannot be rejected. Hence, there is no evidence of conditional heteroskedasticity, and the residuals exhibit a constant variance over time.

Histogram Normality Test

This test for residuals in a EGARCH model is applied to assess whether the model has appropriately captured conditional heteroskedasticity and whether the established residuals are supposed to be normally distributed, thus stating that the model is properly defined.

Table 5

Jarque-Bera Normality Test Result

statistic	**Value**
JB – statistic	5.026
P – value	.081

Jarque-Bera Normality test result in Table 5 shows that the Jarque–Bera statistic (p = .081) is slightly above the .05 significance level, indicating that the residuals are not perfectly normal but close enough. This suggests a mild deviation from normality, and overall, the residuals can be considered approximately normal for the model's analytical purposes.

Ljung–Box Q-statistics and Correlogram Test

The residuals are analyzed through the Ljung–Box *Q*-statistics and correlogram test for indications of autocorrelation.

Table 6

The Ljung–Box Q-statistics and Correlogram Results

Lag	AC	PAC	*Q*-Statistic	*p*-Value
1	0.004	0.004	0.00036	*P* = .952
2	0.0051	0.051	0.6010	*P* = .740
3	-0.027	-0.028	0.7691	*P* = .857
4	-0.115	-0.118	3.7724	*P* = .438
5	0.099	0.105	6.0349	*P* = .303
6	-0.037	-0.028	6.3521	*P* = .385
7	-0.006	-0.024	6.3595	*P* = .498
8	-0.052	-0.056	6.9798	*P* = .539
9	0.014	0.041	7.0280	*P* = .634
10	-0.068	-0.084	8.1155	*P* = .618
15	-0.047	-0.015	10.061	*P* = .816

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20	0.108	0.093	14.975	*P* = .778
25	0.035	-0.025	18.581	*P* = .817
30	-0.001	-0.005	21.040	*P* = .887
35	-0.094	-0.065	28.841	*P* = .759
36	-0.003	-0.001	28.843	*P* = .796

All *p*-values are above the 5% level of significance in the Ljung–Box *Q*-statistics and correlogram result presented in Table 6, and it found no autocorrelation and partial autocorrelation in the residuals as their coefficients remain smaller, which confirms that the model is well-specified and dynamically adequate.

Overall EGARCH Diagnostic Test Results

From the above results, it is clear that the EGARCH model residuals pass all key diagnostic tests. Ljung–Box *Q*-statistics and correlograms show no serial correlation. The Jarque–Bera (p = .081) indicates only minor deviation from normality. The *F*-value of 0.003 (p = .95) for the ARCH-LM results reveal no conditional heteroskedasticity. Together, these tests demonstrate that the EGARCH model is stable, correctly specified, and suitable for reliable inference.

Variance Decomposition of Shocks and Impulse Response Function Test

The Variance Decomposition (VDC) and Impulse Response Function (IRF) are key tools in VAR models to analyze and interpret the dynamic interactions between the selected variables. VDC calculates the effect of each factor on the NEPSE forecast error variance, stating in what way shocks in independent variables can influence its variability over time (Lütkepohl, 2005; Sims, 1986). IRF tracks how a single shock affects any individual variable in NEPSE and other macroeconomic indicators over future periods, revealing the magnitude, direction, and duration of responses (Sims, 1980; Hamilton, 1994). The VDC and IRF models are specified as:

$$y_t = A_0 + A_1 y_{t-1} + A_2 y_{t-2} + \cdots \dots \dots + A_p y_{t-p} + u_t \tag{4}$$

Here, y_t denotes the vector of endogenous variables ($NEPSE_t$,MS_t, CPI_t, TBR_t,), vector of error term denoted by A_0. $A_1, A_2, \dots, A_p$ are coefficient-based matrices, and u_t known as the error term.

Variance Decomposition Analysis

Assessing the relative significance of internal market shocks is done through the adoption of variance decomposition (VDC) estimation versus external economic factors in driving stock market fluctuations over time, and Table 7 presents the results of the variance decomposition analysis of the study.

Table 7

Variance Decomposition Analysis

Variance Decomposition of ΔlnNEPSE					
Period	S.E.	ΔlnNEPSE	ΔlnMS	ΔlnCPI	lnTBR
1	0.030451	100.000	0.000000	0.000000	0.000000
2	0.031037	98.52311	0.514099	0.073474	0.889313
3	0.031209	97.56176	0.581709	0.082369	1.774163
4	0.031335	96.81576	0.640437	0.084832	2.458975
5	0.031429	96.26055	0.680825	0.086493	2.972134
6	0.031499	95.84551	0.711166	0.087684	3.355637
7	0.031552	95.53488	0.733819	0.088573	3.642724
8	0.031592	95.30193	0.750810	0.089240	3.858019
9	0.031622	95.12698	0.769570	0.089740	4.019708
10	0.031645	94.99545	0.773163	0.090116	4.141269

The VDC of the Nepal Stock Exchange index demonstrates that the primary force that drives the stock market is previous innovations of its own, particularly in the short run. In the first forecast period, NEPSE explains 100 per cent of the forecast error variance, itself from its own shocks, highlighting that immediate fluctuations are completely self-generated. In the second and third periods, the share of its own innovations slightly decreased to around 98.52% and 97.56%, respectively, as external macroeconomic variables started to exert a minor influence.

Among these, the treasury bill rate begins to become the most important factor, contributing 0.89% in period 2 and 1.77% in period 3, while money supply and inflation show small effects on the NEPSE Index. As the horizon extends to the medium run from period 4 to period 7, the contribution of NEPSE's own shocks declines gradually, falling from 96.81% in period 4 to 95.53% in period 7. The influence of the treasury bill rate rises steadily, reaching 3.64% by period 7, confirming its growing importance in shaping market behaviour. The influence of money supply increased to about 0.73% in period 7, but inflation remains negligible, with its contribution being just 0.08%. This indicates that internal market dynamics remain dominant and the macroeconomic variables, particularly interest rates, play a noticeable role as the period extends.

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In conclusion, the Nepal Stock Exchange is mostly self-determined, with its own shocks explaining approximately 95% of fluctuations even in the long run however, the interest rate emerges as the most influential macroeconomic factor among all, with its contribution increasing to over 4% by the end of period 10, stating that the stock market is sensitive to interest rate movements, and the remaining two variables, money supply and inflation, possess a very small role in stock index fluctuations.

Impulse Response Function Analysis

IRF assessment examines exactly how one-time shock to a macroeconomic variable or NEPSE itself affects both the present and the future of every single parameter in the framework by offering insights into the magnitude, direction, and duration of the responses, revealing the stock market and its dynamic interactions with key indicators of economy, and the findings of the IRF analysis of the study are displayed in Table 8.

Table 8

Impulse Response Function Analysis

Impulse Response of ΔLnNEPSE				
Period	ΔLnNEPSE	ΔLnMS	ΔLnCPI	LnTBR
1	0.030451	0.000000	0.000000	0.000000
2	0.004668	0.002225	-0.000841	-0.002927
3	0.001114	0.000845	-0.000307	-0.002952
4	0.000585	0.000789	-0.000175	-0.002620
5	0.000451	0.000661	-0.000146	-0.002283
6	0.000385	0.000576	-0.000125	-0.001984
7	0.000333	0.000499	-0.000109	-0.001723
8	0.000289	0.000434	-9.43E-05	-0.001497
9	0.000251	0.000377	-8.19E-05	-0.001300
10	0.000218	0.000327	-7.11E-05	-0.001129

The impulse response function (IRF) analysis of Nepal Stock Exchange index provides important insights in the first period, stock index shown periods immediate positive response to its own shock 0.030451, stating that the present fluctuation in the stock confirming that stock price dynamics are primarily self-driven in the very short run and this effect diminishes in subsequent periods, falling to 0.004668 in period 2 and to 0.000218 when reaching to period 10 suggesting that while self-innovations initially dominate, their influence and that weakens over time as the effects of external macroeconomic factors gradually appear.

The responses to macroeconomic variables exhibit more complex behaviour. Money supply begins with no immediate effect but exerts a positive effect with 0.002225 from period 2 onward, although the magnitude is minimal and declines steadily to 0.000327 in period 10. Inflation continuously exerts a negative influence with –0.000841 in period 2 and gradually weakens over time. This suggests that rising consumer prices weaken stock market performance. The treasury bill rate has the most significant and consistent negative impact on the NEPSE index among macroeconomic variables, and this effect continues throughout the forecast. It exhibits a continuous negative response, beginning with -0.002927 in period 2 and gradually declining to -0.001129 in period 10. This persistent negative reaction implies that higher interest rates negatively impact market returns by reducing equity investment. Hence, the Nepalese stock market depends heavily on its own shocks in the short run, and its effect diminishes over time as external macroeconomic variables start to influence the stock index. This result states that among all the macroeconomic variables, money supply contributes positively but only marginally, while inflation interest rates and consistently exert negative effects on the Index, being more influential in the later periods.

Overall, the findings establish that the Nepalese stock market is driven in the short term by its own innovations. The treasury bill rate has the highest and persistent influence among the key macroeconomic drivers of NEPSE volatility while money supply plays a moderate positive role and inflation has only a marginal negative effect.

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Conclusion and Recommendation

To capture patterns of volatility and returns, the study assesses how NEPSE interacts with the selected macroeconomic factors. The EGARCH analysis of the NEPSE index shows that the stock market of Nepal exhibits asymmetric, mean-reverting, and persistent volatility with excessive volatility clustering, where negative shocks generate greater fluctuations than the positive shocks of the same size. Only the treasury bill rate significantly influences the stock returns, while money supply and inflation remain statistically insignificant. This result align with earlier research on the leverage effects reflects by the asymmetric GARCH-type model (Dangal & Gajurel, 2021; Erdem et al., 2005) and persistent and time-varying volatility in developing and emerging economies (Basher et al., 2007; Gaire, 2017; Rana, 2020). Besides these, the findings align with the studies emphasizing the importance of macroeconomic determinants like interest rates and inflation, which drive the stock market fluctuations (Mukhopadhyay & Sarkar, 2003; Kirui et al., 2014).

Variance Decomposition (VDC) analysis clearly states that NEPSE is largely self-driven, with its own shocks explaining approximately 95%, while the treasury bill rate exerts the largest external impact, rising to 4.14% by period 10. Money suppy exerts a minor positive effect, and inflation shows a consistently negative but negligible impact indicating that interest rate changes play the most influential role in explaining stock market variability over time. Similarly, impulse responses confirm that NEPSE reacts strongly to its own innovations in the early periods and declines over time, while TBR and CPI shocks exert persistent negative effects, showing that NEPSE's short-term dynamics are driven by internal market factors, and its medium- and long-term behaviour is increasingly influenced by macroeconomic variables. From both VDC and IRF results, the treasury bill rate emerges as the most influential macroeconomic factor, implying its growing role in influencing market volatility and long-term stock market behaviour in Nepal.

In conclusion, NEPSE exhibits asymmetric, mean-reverting and persistence of volatility, heavily influenced by negative shocks and largely self-regulated in the short-run market. Investors are recommended to consider self-driven, shock-sensitive volatility and the negative impact of treasury bill rates when planning investments, while policymakers need to maintain stable interest rates, control inflation, and ensure consistent monetary policy to support market stability and growth.

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