Nepalese Stock Market Volatility Using ARCH and GARCH Models

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Abstract

This article analyzes the volatility process of the series of returns of Nepal Stock Exchange (NEPSE) through time series econometric models. This article applies ARCH (2) and GARCH (1, 1) on NEPSE index from 2020 to 2025, which is on a daily frequency. Stationarity tests through Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests make the return series stationary. ARCH tests determine the presence of autoregressive conditional heteroskedasticity effects as an attempt to validate the presence of long-run clustering volatility. ARCH (2) and GARCH (1, 1) describe volatility. In ARCH (2), it is proved that previous squared errors form an adequate description of current volatility across time in such a manner that recent shocks matter more than the previous shocks. The GARCH (1, 1) model also indicates high volatility persistence, wherein future market movement is significantly dependent on previous volatility. The results suggest that returns in NEPSE are volatile clustered, i.e., there will be continued high volatility. The findings are of significant policy implication for risk-averse investors and policy makers, wherein there is a need to apply suitable risk management measures in the Nepalese stock market.

Keywords: Volatility clustering, Risk, NEPSE, ARCH models, GARCH models

Introduction

Stock market volatility is the amplitude of the movement in the share prices in the course of a given interval of time. Too much is undesired since any amount is intrinsic to prices movements, indicating unanticipated adjustments, but substantial ones create asset uncertainty, loss of investor trust and confidence, because risk-neutral investors or even those who avoid taking risks might opt to withdraw their money at moments of abrupt falls or rapid upward surges of prices. Such wild volatility can also disrupt the usual functioning of the stock market. (Cortes &Weidenmier, 2017)

Investors and market participants are highly concerned with investment risk. Asset volatility modeling and forecasting are important in portfolio management and risk

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evaluation. Therefore, scholars and practitioners have developed various models to forecast and model asset volatility. Volatility, sometimes referred to as the time-varying variance of asset returns, is a measure of financial asset risk. One of the key features of financial markets is volatility clustering, where periods of high market volatility are followed by long-horizon high volatility, and peaceful times are followed by long-run stability (Tsay, 2010).Financial time series can also have properties such as negative skewness, excess kurtosis, and persistence of conditional variance (Andersen, Bollerslev, Diebol, & Ebens, 2001). The stylized facts contradict the normality and linearity assumptions of traditional models of finance. Certain studies in an attempt to propose that financial return distributions have fat tails, occasionally approaching a Cauchy distribution or with moments of infinite size (Mandelbrot, 1963).

In order to capture these nonlinearities, researchers have used advanced econometric models. Conditional mean nonlinearities are modeled by researchers with the help of threshold autoregressive (TAR) or Markov-switching models. However, if the nonlinearity results from conditional variance, then the right approach to follow is the Autoregressive Conditional Heteroskedasticity (ARCH) model introduced by (Engle, 1982). The model attempts to model time-varying volatility by modeling the current variance as a function of lagged squared residuals. (Bollerslev, 1986) Subsequently developed the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model that allows for persistence of volatility effects over time. The GARCH model has been subsequently generalized, such as asymmetric forms EGARCH and GJR-GARCH, to better model volatility dynamics.

This ongoing study utilizes ARCH and GARCH models to incorporate NEPSE return volatility with empirical findings from their risk profile. Though extensive studies have taken place, mainly in developed countries, not as much has been done in an emerging economy like Nepal. By mentioning volatility clustering and NEPSE return persistence, the current study presents the enhanced understanding of risk profiles from an emerging financial market.

The remaining part of the paper adopts this structure: Section 2 Literature Review, Section 3 Statement of the problem, Section 4 Research objective, Section 5 Methodology, Section 6 Results and discussion, and Section 7 concludes the study with findings and implications.

Literature Review

Numerous studies have employed GARCH-type models and other approaches to analyze financial asset volatility. This paper aims to investigate the volatility dynamics of the NEPSE Index, with a particular focus on reviewing prior research on this index. Additionally, we begin by briefly examining studies that explore stock index volatility in emerging and developing markets. (Abdalla& Winker, 2012) Analyzed the volatility of the Egyptian and Sudanese stock markets from January 2006 to November 2010 using symmetric and asymmetric GARCH models. Their findings indicate that return volatility in both markets is highly persistent and exhibits explosive characteristics. Similarly, (Ugurlu, Thallassines, & Murateglu, 2014) applied GARCH, GJR-GARCH, and EGARCH models to stock indices in five European emerging markets—Turkey, Bulgaria, the Czech Republic, Poland, and Hungary. Their study reveals that volatility shocks in these markets are persistent and that past information significantly impacts current volatility. (Koy&Ekim, 2016) Used GARCH, EGARCH, and TGARCH models to examine the volatility of Borsa Istanbul sub-indices (2011–2014). Their results show no significant asymmetric impact of shocks on banking stocks, whereas other sub-indices exhibit asymmetric volatility patterns.

Several studies have focused specifically on Nasdaq-100 volatility. (Lu & Perron, 2010) Incorporated a random level shift model into GARCH to forecast volatility in four U.S. stock indices, including Nasdaq, finding that the level shift model better captures long-memory effects and conditional heteroscedasticity compared to the standard GARCH (1, 1) model. (Carlin & Lam, 2011) Addressed limitations in (Andersen & Bollerslev, 1997) sequential estimation method for intraday volatility modeling. Using 10-minute returns of the Nasdaq Composite index (August 2005 – September 2008), they developed an approach that accounts for both periodicity and heteroscedasticity interactions. (Chin, Yu, & Zivot, 2012) Examined the volatility of 30 actively traded Nasdaq stocks, incorporating after-hours trading information into a GARCH model. Their results show that pre-market coefficients are positive and significant for 23 of the 30 stocks, while post-market variance has limited predictive power for future volatility.

Further studies have investigated long-memory effects and alternative modeling approaches. (Caporale & Gil-Alana, 2012) Analyzed Nasdaq-100 volatility persistence using daily data (January 2001 – February 2004). Applying a Gaussian semi parametric method, they found that Nasdaq-100 volatility exhibits long memory, with shocks fading over time while maintaining mean-reverting properties. (Molnár, 2016)used the Range-GARCH (1,1) model to study six stock indices, including Nasdaq-100, concluding that Nasdaq-100 volatility is highly persistent ($\alpha + \beta = 1.028$) and that R-GARCH outperforms the standard GARCH(1,1) in forecasting, although it does not capture the leverage effect. (Augustyniak, Bauwen, & Dufays, 2019) Introduced the Factorial Hidden Markov Volatility model, demonstrating its superiority in modeling and forecasting Nasdaq-100 return volatility in both the short and long run.

Recent studies continue to refine volatility modeling techniques. (Altun, 2017) Incorporated a two-sided Lomax distribution into a GJR-GARCH model to improve value-at-risk (VaR) forecasting. Using daily Nasdaq-100 data (March 2014 – April 2018), he found that the GJR-GARCH model under this distribution more accurately models skewness and excess kurtosis. Chang et al. (2019) proposed a modified Grey-GARCH model to examine Nasdaq closing price volatility, demonstrating that their approach outperforms standard Grey-GARCH and GARCH models.

This paper contributes to the literature by modeling NEPSE index volatility using GARCH models over the period of 2020 to 2025. By incorporating a long-term perspective and evaluating various volatility dynamics, this study provides new insights into the behavior of NEPSE index.

Statement of the Problem

The problem at hand is the impact of volatility on stock market return in the Nepalese stock market. That is, it seeks to explain how changes in market volatility influence the performance and returns of stocks within this market.

Research Objective

The objective of this study is to assess the volatility on the daily stock market returns of the Nepalese Stock Exchange.

Research Hypothesis

Ho: There is no existing ARCH effect up to the specified lag/ there is no significant volatility on stock returns in the Nepalese stock market.

Methodology

The study employs a quantitative ex-post facto was the research approach utilized. For social and education research, "ex-post-facto" or "retrospective" refers to study research that tests for potential cause-and-effect when looking at some present condition or occurrence and scanning backward in history for potential cause without manipulation or intervention by the researcher. Essentially, researchers are seeking to discover those factors that can be associated with some occurrences, conditions, or behaviors.

Secondary data is data that has been collected by someone else for purposes other than the current research. Its use in this research is legitimate as it can be acquired easily, at low cost, and saves time compared to collecting primary data. Secondary data can be more accurate, help develop research problems and hypotheses, and help in the identification of the population. The data was collected from the NEPSE alpha from the period 2020 to 2025 for this research.

The study utilize day-by-day NEPSE index price data of 2020-2025 to calculate the returns volatility of the index. Data is provided by NEPSE Alpha. We use return (rt) data for the sake of reducing change range and heteroscedasticity and define it by taking the time t price (pt)/the past price (pt-1) and the natural log. And that's the logarithmic first difference.

$rt = ln\ (pt/pt{-}1)$ where *rt*is the daily return, *pt*and*pt-1* denote the index price for the day *t* and *t-1* respectively.

Returns on financial markets are generally time-varying in their volatility, and therefore the traditional autoregressive (AR) and moving average (MA) models with constant conditional variance are not adequate to capture nonlinear behavior. Linear models cannot identify the most critical properties of financial time series, such as volatility clustering, leverage effects, leptokurtosis, and long memory (Zivot, 2009). Therefore, an econometric model capable of addressing non-constant volatility is needed to model financial market fluctuations accurately. The ARCH model of (Engle, 1982) and the extensions thereof are widely used for modeling and forecasting asset price volatility. (Bollerslev, 1986) expanded this further by including both the moving average (MA) and the autoregressive (AR) terms into the conditional variance specification to derive the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The GARCH (p, q) model provides a more flexible framework for capturing the persistence and clustering effects commonly observed in financial markets.

Since financial markets data often exhibit varying volatility, autoregressive (AR) and moving average (MA) models, that assume the conditional variances are constant, cannot capture the nonlinear dynamics. Linear models are unable to explain characteristics like volatility clustering, leverage effects, leptokurtosis and long memory in financial series (Zivot, 2009).Thus, we employ an econometric method that allows modeling nonlinear patterns as non-constant volatility.

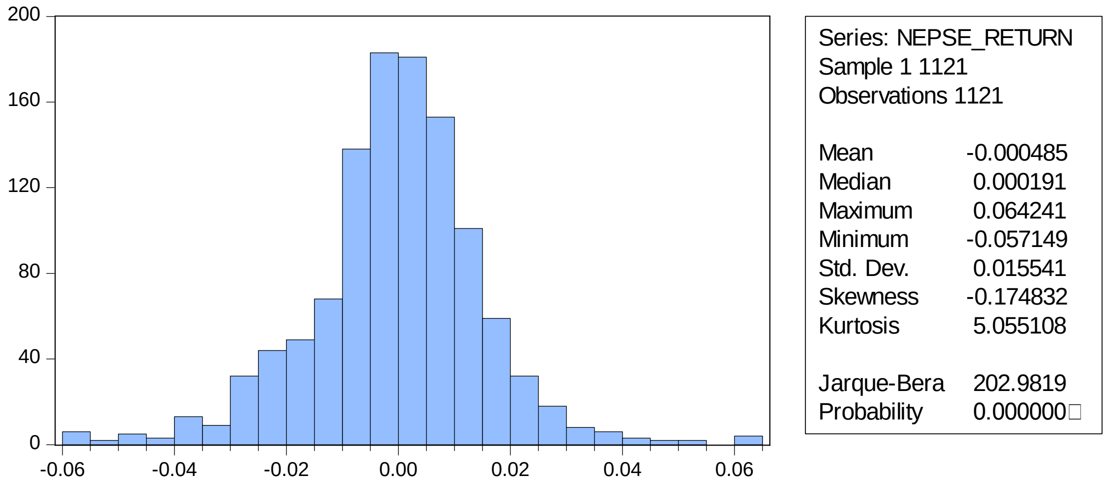
Autoregressive conditional heteroscedasticity (ARCH) and its derivative models are popularly utilized in modelling and forecasting asset dynamics. (Bollerslev, 1986) Extended (Engle, 1982) and developed the technique that allows for both autoregressive (AR) and moving average (MA) components in the heteroskedastic variance. This is the generalized Autoregressive Conditional Heteroscedasticity, GARCH (p, q) model.

Results and Discussions

In this study, we used the ARCH/GARCH model to assess the presence of volatility in stock returns. Many time series variables, especially asset prices, tend to follow a random walk pattern, making it difficult to predict their future movements. However, these variables often display predictable patterns of volatility. Therefore, the square of the change in an asset's price serves as a measure of its volatility. Standard time series methods can model these volatility patterns, with the key distinction being that volatility is treated as the dependent variable. The ARCH models provide a more formal approach to measuring volatility, consisting of two equations: one is a standard regression equation, and the other is a volatility equation, where volatility is defined as the time-varying variance of the regression error. Similar to AR models, the ARCH models focus on the volatility equation. In this study, we estimated the ARCH and GARCH models using Eviews software.

The 1121 observations in the *rt*series have a mean value of -0.000485 and a sample standard deviation of 0.01541. Table 1 reports descriptive statistics of the data. The distribution of returns remarkably differs from normality given the excess kurtosis and light right skewness implying some asymmetry. Heavy tailed leptokurtic distribution implies the index has low risk and return in the sample space. Consequently, based on the Jarque-Bera statistic, the null hypothesis of normality for the daily NEPSE return is rejected at the 5% significance level.

Table 1: *Descriptive statistics of Nepse return series*



From the results of summary statistics and normality measures reported in Table 1 observe that the daily mean return is negative indicating loss in the stock market during the trading period under consideration. The high values of the daily range return and the standard deviation show a high level of variability of price changes in the Nepalese stock market. The skewness of the stock market return series of NEPSE is Negative indicating that the stock index returns are flatter and skewed to the left as compared to the normal distribution.The result implies the return series extends towards negative values than positive.The kurtosis value of the returns of Nepalese market was very high, which indicates that the stock returns distribution have sharp peak when compared to a normal distribution. The result implies that the return distribution is heavy tailed. The result of Jarque-Bera Statistic of the daily return series is not normal due to the probability is less than 0.05.

Table 2: *Unit root test results*

Null hypothesis: Return series has a unit root.

	T statistic	Critical values at 5% level	Probability
ADF test statistic	-17.49109	-2.861943	0.0000
PP test statistic	-31.07410	-2.861943	0.0000

Stationarity of the series is tested with Augmented Dickey-Fuller and Phillips-Perron unit root tests and reported on Table 2. Both test results reject null hypothesis that the return series has not a unit root and that means the NEPSE return series is stationary in the period under study.

Table 3: *Results of test for ARCH effect*

Ho: There is no ARCH effects

Variable	Coefficient	t-statistic	Probability
C	0.000179	11.43339	0.0000
RESID^2(-1)	0.249538	8.616850	0.0000

Test for ARCH effects' findings indicate that the null hypothesis (H_0: There is no ARCH effect) should be rejected at a high level of significance. Constant (C) is highly significant (p = 0.0000) and is equal to 0.000179, which is a stable variance term. Above all, the lagged squared residual term $RESID^2$ (-1) also possesses a positive coefficient of 0.249538 and is extremely significant (p = 0.0000), confirming the presence of autoregressive conditional heteroskedasticity (ARCH) effects. This shows that past volatility influences present volatility, whereby market returns are volatile clustering—periods of high volatility are followed by more volatility. Considering these findings, using ARCH or GARCH models to model market volatility is warranted.

As noted above, Arch-effect is present if the coefficient of the lagged residual squared (U2 t-1) is positive and if the estimate is significant. From table 3, the coefficient of U2 t-1 is positive. In addition, according to the t-test as well as F-test and Chi-square test, the estimate is significant at the 5% level. Therefore, the null hypothesis that there is no arch-effect is rejected. Therefore, it is concluded that Arch-effect exists.

Having established that Arch-effect does indeed exist, the ARCH (2) model is used. The result of this exercise is outlined in table 4.

Table 4: *Results of ARCH (2) Model for Market Volatility*

Mean Equation			
Variable	Coefficient	Z-statistic	Probability
C AR(1) MA(1	-0.000670 -0.322954 0.508687	-1.381601 -2.809645 5.003439	0.1671 0.0050 0.0000
Variance Equation			
C RESID(-1)^2 RESID(-2)^2	0.000141 0.230288 0.181605	17.40521 5.271699 5.355591	0.0000 0.0000 0.0000

The results of the ARCH (2) model for market volatility are presented in Table 4, showing both the mean and variance equations. In the mean equation, the constant (C) has a negative coefficient of -0.000670, but it is not statistically significant (p = 0.1671). The autoregressive term AR (1) has a coefficient of -0.322954 and is significant at the 1% level (p = 0.0050), indicating a negative relationship between past and current values. The moving average term MA (1) is positive (0.508687) and highly significant (p = 0.0000), suggesting a strong short-term persistence in returns.

In the variance equation, the constant (C) is positive (0.000141) and highly significant (p = 0.0000). The first and second lag of squared residuals (RESID (-1) ^2 and RESID (-2) ^2) have positive coefficients (0.230288 and 0.181605, respectively), both statistically significant at the 1% level. This indicates that past shocks have a lasting impact on market volatility, with recent shocks (RESID (-1) ^2) having a stronger effect than older ones (RESID (-2) ^2). Overall, the results suggest that market volatility exhibits clustering, where periods of high volatility tend to be followed by further volatility. On the basis of this, the conclusion is that stock market returns in Nepal exhibit volatility clustering. Knowledge of such periods of high volatility is important to risk-averse investors.

This analysis is extended further to accommodate a scenario where the variability in the series changes more slowly than in the ARCH (1, 1) model especially in emerging markets. Consequently, a GARCH (1, 1) model is implemented. This allows the variance scaling parameter to depend on both the past value of the shock and past value of itself.

Table 5: *Results of GARCH (1.1) Model for Market Volatility*

Mean Equation			
Variable	Coefficient	Z-statistic	Probability
C	-0.000770	-1.718234	0.0858
AR(1)	-0.439888	-2.965504	0.0030
MA(1)	0.585118	4.325220	0.0000
Variance Equation			
C	1.55E-05	4.915039	0.0000
RESID (-1)2	0.132555	6.741582	0.0000
GARCH(-1)	0.803143	30.62413	0.0000

The results of the GARCH (1, 1) model for market volatility, presented in Table 5, show both the mean and variance equations. In the mean equation, the constant (C) has a negative coefficient of -0.000770 but is not statistically significant (p = 0.0858). The autoregressive term AR (1) has a negative coefficient of -0.439888 and is significant at the 1% level (p = 0.0030), indicating that past values negatively influence current returns. The moving average term MA (1) is positive (0.585118) and highly significant (p = 0.0000), suggesting a strong short-term persistence in returns.

In the variance equation, the constant (C) is small (1.55E-05) but statistically significant (p = 0.0000). The lagged squared residual term RESID (-1) ^2 has a positive coefficient of 0.132555, significant at the 1% level, indicating that past shocks contribute to current volatility. The GARCH (-1) term, representing the persistence of past volatility, has a large and highly significantcoefficient (0.803143, p = 0.0000), suggesting that volatility is highly persistent over time. The sum of RESID (-1) ^2 and GARCH (-1) is close to 1, implying a long memory in volatility, meaning that market shocks have a prolonged effect on future volatility. This confirms the presence of volatility clustering, where periods of high volatility are followed by further volatility.

Conclusion

Most financial time series are autocorrelated and volatility clustered, which violate common econometric assumptions. ARCH (2) and GARCH (1, 1) models are used in this study to analyze the volatility of NEPSE index returns from 2020 to 2025. The models robustly capture the volatility clustering of the return series. To the best of our knowledge, there is no such study that investigated the dynamics of NEPSE's daily index return volatility exhaustively.

The findings reveal that NEPSE index returns are not normally distributed and exhibit volatility clustering, with varying variances of residuals. The results validate the existence of a nonlinear trend in conditional variance of returns, which can be modeled using the GARCH (1, 1) model. The estimates of ($\alpha 1 + \beta 1$) reveal that variance of the series exhibits long memory, with the volatility shocks being highly persistent.

References

Abdalla, S., & Winker, P. (2012). Stock market volatility using univariate GARCH model: Evidence from Suden and Egypt. *International Journal of Economics and Finance*, 161-176.

Altun, M. (2017). Forecasting value-at-risk with two-step method: Garch-exponentiated odd Log-Logistic normal model,. J*ournal for Economic Forecasting, Institute for Economic Forecasting,*, 97-115.

Andersen, T. G., B. , Diebol, F. X., & Ebens, X. (2001). The distribution of realized stock return volatility. *Journal of Financial Economics*, *61*(1), 43-76, doi:10.1016/S0304-405X(01)00055-1.

Andersen, T., & Bollerslev, T. (1997). Intraday periodicity and volatility persistence in financial markets. *Journal of Empirical Finance*, 115-158.

Augustyniak, M., Bauwen, L., & Dufays, P. (2019). *A New Approach to Volatility Modeling: The Factorial Hidden Markov Volatility Model,*, 696-709.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroscedasticity. *Journal of Econometics*, 307-327.

Caporale, G. M., & Gil-Alana, L. A. (2012). Estimating persistence in the volatility of asset returns with signal plus noise models. *International Journal of Finance and Economics*, 23-30.

Carlin, C., & Lam, K. (2011). Modeling intraday volatility: A new consideration. *Journal of International Financial Markets, Institutions and Money,*, 388-418.

Chin, C., Yu, W., & Zivot, E. (2012). Predicting stock volatility using after-hours information: Evidence from the NASDAQ actively traded stocks. *International Journal of Forecasting*.

Cortes, G. S., & Weidenmier, M. D. (2017). *Stock volatility and the great depression* (NBER Working Paper No. 23554). National Bureau of Economic Research. https://www.nber.org/papers/w23554

Engle, R. (1982). Autoregressive conditional heteroscedasticity with estimates of the Variance of United Kingdom Inflation. *Econometria*, 987-1007

Koy, Ayben and Ekim, Samiye, (2016) Borsa istanbul sektör endekslerinin volatilite modellemesi. *Trakya Üniversitesi İktisadi ve İdari Bilimler Fakültesi E-Dergi*, , 205-219 ,: https://ssrn.com/abstract=2991912.

Lu, Y., & Perron, P. (2010). Modeling and forecasting stock return volatility using a random level shift model,. *Journal of Empirical Finance*, 138-156.

Mandelbrot, B. (1963). The variation of certain speculative prices. The Journal of Business, *36*(4), 394- 419. Retrieved from http://www.jstor.org/stable/2350970. *The Journal of Business*, 394-419 Retrieved from http://www.jstor.org/stable/2350970 Nasdaq: NDX vs SPX (2019, August 5) .

Molnár, P. (2016). High-low range in GARCH models of stock return volatility *Applied Economics*, 977-991.

Tsay, R. (2010). *Analysis of Financial Time Series,3rd Edition.* New York, United States of America,: John Wiley & Sons, Inc. DOI: 10.1002/9780470644560.

Ugurlu, E., Thallassines, E., & Murateglu, Y. (2014). Modelling volatilityin the stock markets using GARCH Models: Europipean emerging economics and Turkey. *International Journal of Economics and Business Administration*, 72-87.

Zivot, E. (2009). Practical Issues in the analysis of univariate GARCH Models. *Mikosch*, 201-234.

Appendices

Appendix 1

Null Hypothesis: NEPSE_RETURN has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=21)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-17.49109	0.0000
Test critical values:	1% level	-3.435983	
	5% level	-2.863915	
	10% level	-2.568086	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(NEPSE_RETURN)
Method: Least Squares
Date: 02/01/25 Time: 08:10
Sample (adjusted): 4 1121
Included observations: 1118 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
NEPSE_RETURN(-1)	-0.872001	0.049854	-17.49109	0.0000
D(NEPSE_RETURN(-1))	-0.045377	0.040513	-1.120050	0.2629
D(NEPSE_RETURN(-2))	-0.106156	0.029792	-3.563240	0.0004
C	-0.000427	0.000462	-0.924368	0.3555
R-squared	0.470857	Mean dependent var		-4.68E-06
Adjusted R-squared	0.469432	S.D. dependent var		0.021181
S.E. of regression	0.015428	Akaike info criterion		-5.501648
Sum squared resid	0.265170	Schwarz criterion		-5.483690
Log likelihood	3079.421	Hannan-Quinn criter.		-5.494859
F-statistic	330.4301	Durbin-Watson stat		2.004280
Prob(F-statistic)	0.000000			

Appendix 2

Null Hypothesis: NEPSE_RETURN has a unit root
Exogenous: Constant
Bandwidth: 11 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-31.39039	0.0000
Test critical values:	1% level	-3.435973	
	5% level	-2.863911	
	10% level	-2.568083	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000240
HAC corrected variance (Bartlett kernel)	0.000286

Phillips-Perron Test Equation
Dependent Variable: D(NEPSE_RETURN)
Method: Least Squares
Date: 02/03/25 Time: 13:09
Sample (adjusted): 2 1121
Included observations: 1120 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
NEPSE_RETURN(-1)	-0.926994	0.029832	-31.07410	0.0000
C	-0.000449	0.000464	-0.968696	0.3329

R-squared	0.463429	Mean dependent var	-6.57E-06
Adjusted R-squared	0.462949	S.D. dependent var	0.021168
S.E. of regression	0.015513	Akaike info criterion	-5.492505
Sum squared resid	0.269047	Schwarz criterion	-5.483539
Log likelihood	3077.803	Hannan-Quinn criter.	-5.489116
F-statistic	965.5999	Durbin-Watson stat	1.991580
Prob(F-statistic)	0.000000		

Appendix 3

Heteroskedasticity Test: ARCH

F-statistic	74.25009	Prob. F(1,1118)	0.0000
Obs*R-squared	69.75055	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 02/12/25 Time: 19:47
Sample (adjusted): 2 1121
Included observations: 1120 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000179	1.57E-05	11.43339	0.0000
RESID^2(-1)	0.249538	0.028959	8.616849	0.0000

R-squared	0.062277	Mean dependent var	0.000239
Adjusted R-squared	0.061439	S.D. dependent var	0.000485
S.E. of regression	0.000470	Akaike info criterion	-12.48475
Sum squared resid	0.000247	Schwarz criterion	-12.47578
Log likelihood	6993.460	Hannan-Quinn criter.	-12.48136
F-statistic	74.25009	Durbin-Watson stat	2.100244
Prob(F-statistic)	0.000000		

Appendix 4

Dependent Variable: RETURNS
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 02/13/25 Time: 18:03
Sample (adjusted): 2 1121
Included observations: 1120 after adjustments
Convergence achieved after 22 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 1
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*RESID(-2)^2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000670	0.000485	-1.381601	0.1671
AR(1)	-0.322954	0.114945	-2.809645	0.0050
MA(1)	0.508687	0.101667	5.003439	0.0000
		Variance Equation		
C	0.000141	8.07E-06	17.40521	0.0000
RESID(-1)^2	0.230288	0.043684	5.271699	0.0000
RESID(-2)^2	0.181605	0.033909	5.355591	0.0000

R-squared	0.002562	Mean dependent var	-0.000484
Adjusted R-squared	0.000776	S.D. dependent var	0.015547
S.E. of regression	0.015541	Akaike info criterion	-5.604041
Sum squared resid	0.269795	Schwarz criterion	-5.577142
Log likelihood	3144.263	Hannan-Quinn criter.	-5.593874
Durbin-Watson stat	2.204315		
Inverted AR Roots	-.32		
Inverted MA Roots	-.51		

Appendix 5

Dependent Variable: RETURN
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 02/12/25 Time: 20:10
Sample (adjusted): 2 1121
Included observations: 1120 after adjustments
Convergence achieved after 32 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 1
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000770	0.000448	-1.718234	0.0858
AR(1)	-0.439888	0.148335	-2.965504	0.0030
MA(1)	0.585118	0.135280	4.325220	0.0000

	Variance Equation			
C	1.55E-05	3.15E-06	4.915039	0.0000
RESID(-1)^2	0.132555	0.019662	6.741582	0.0000
GARCH(-1)	0.803143	0.026226	30.62413	0.0000

R-squared	0.009188	Mean dependent var	-0.000484
Adjusted R-squared	0.007414	S.D. dependent var	0.015547
S.E. of regression	0.015490	Akaike info criterion	-5.639402
Sum squared resid	0.268003	Schwarz criterion	-5.612503
Log likelihood	3164.065	Hannan-Quinn criter.	-5.629235
Durbin-Watson stat	2.123223		

Inverted AR Roots	-.44
Inverted MA Roots	-.59