The International Research Journal of Management Science

Print - ISSN 2542-2510
E-ISSN 2717-4867
Vol. 9, Issue 1 -Dec 2024
http://www.ncm.edu.np

Structural Change and Diagnosis of Nepalese Stock Market Volatility

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Received on : 10th July, 2024
1st Revised : 03rd October, 2024
2nd Revised : 25th October, 2024
Accepted on: 12th November, 2024
Published on : 18th December, 2024

Cite this paper
Shrestha, B. (2024). Structural Change and Diagnosis of Nepalese Stock Market Volatility. *The International Research Management Science*, Vol. 9 (1), 169-186.

Abstract
Purpose: This paper studies the volatility of the Nepalese stock market. It focuses on two aspects of volatility: persistence and leverage effects. It aims to evaluate whether the presence of deterministic structural shifts in volatility produces biased estimations of persistence and leverage parameters.

Design/Methodology: This study uses time-series econometric modeling. The family of asymmetric GARCH specifications has been used to capture the leverage effect and persistence in the longitudinal univariate time-series indices data. The study covers 13 subindices along with a composite NEPSE index covering the period from 2003 to 2023.

Findings: Findings suggested that the estimates of persistence and leverage parameters are biased when deterministic structural shifts are not considered. Result indicated the downward adjustment of the estimated parameters of leverage and persistence when such structural shifts are incorporated in the models.

Conclusions: Failure to incorporate deterministic structural shifts are expected to produce biased estimate of volatility attributes of high-frequency financial time series data. A downward shift in persistence parameters indicates that the impact of recent lagged conditional variance and information shocks have larger effect on expected volatility compared to that of distant conditional variances. Decrease in leverage parameters in the presence of deterministic structural shifts suggested the reduction in asymmetry of the news impact ('bad news' vs 'good news').

Implications: Investors and researchers when analyzing the high-frequency univariate financial time-series shall incorporate deterministic structural shifts in their analysis to ensure more robust analysis. Understanding the adjusted persistence and leverage parameters allows decision-makers to make informed risk assessments and enables to recalibrate their strategies to respond more promptly to market changes.

Keywords: *Persistence, leverage, deterministic structural shifts, volatility, asymmetric generalized autoregressive conditional heteroskedasticity*

https://doi.org/10.3126/irjms.v9i1.72730

JEL Classification: C22, G32, C52, G14, C58

Introduction

Stock market volatility plays a pivotal role in shaping investment decisions, directly influencing market uncertainty and affecting the behavior of both enterprises and individual investors. The seminal work of Markowitz (1952) and Sharpe (1964) laid a foundation with the systematic effort to formalize the dynamics between risk and return. Investors respond not only to average return but also to the variance of expected return while making investment decision. The variance of return shows the response of investors to various shocks, whether realized or anticipated. Traditional econometric models assumed a constant one-period variance which was implausible assumption. A broader measure of risk that captures the time-varying conditional variance offers more meaningful insights. This led to the systematic effort in modeling an autoregressive conditional heteroskedastic process (Bollerslev, 1986; Engle, 1982). Empirical research has since highlighted the dynamic nature of market volatility, to delve deeper into understanding its patterns and influences (Alberg et al., 2008; Assaf, 2016; Ewing & Malik, 2005; Hamilton & Susmel, 1994; Raddant & Kennett, 2021).

The market inefficiencies present in emerging market allows the historical data to exert informational value while making investment decisions. Several studies were undertaken to systematically understand the volatility attributes of the Nepalese stock market (Dangal & Gajurel, 2021; Dangol & Bhandari, 2019; Rana, 2020) which have been pivotal in characterizing Nepalese capital market. Despite their noble contribution, the failure to incorporate the deterministic structural shifts in their models with high-frequency financial time series data may have resulted in biased estimates of volatility (Abdennadher & Hellara, 2018; Assaf, 2016; Lamoureux & Lastrapes, 1990).

This study provides empirical validation for improving the volatility model by incorporating deterministic structural shifts while diagnosing volatility of Nepalese capital market, addressing the key methodological gap in extant literature. The purpose is to provide a more robust volatility model specification, allowing investors to recalibrate their investment decisions.

The paper is organized into five sections. Section II of this study deals with the review of literature followed by section III outlining the research methodology. Results and findings have been presented in section IV. Final section V presents the implication and conclusion.

Review of Literature

Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models (Bollerslev, 1986) are the pioneer work of literature in understanding volatility patterns, reflecting the inherent clustering and persistence in financial time-series data.

Rana (2020) examined the properties of time-varying volatility of daily stock returns in Nepal over the period of 2011-2020 using 2059 daily return observations of the composite NEPSE index. Using symmetric and asymmetric GARCH family specifications, the findings showed that NEPSE confirmed the persistence of volatility in daily returns over the sample period. Dangal and Gajurel (2021) study on volatility clustering in the NEPSE Index, using similar methods, also revealed a positive association between volatility and the expected return of the NEPSE index in the form of risk premium, confirming the persistence in conditional variance.

The volatility persistence in financial time series allows to make inference regarding the "memory property", which holds considerable significance in volatility analysis. Assaf (2016) examined the volatility attributes in MENA countries both before and after the 2008 financial crisis. The findings highlighted persistence in volatility, using absolute and squared returns, where the returns exhibited a comparatively weaker indication of long memory. With the rise of high-frequency trading in the U.S. capital market, studies (Zhang, 2010) have revealed a positive correlation between high-frequency trading and stock price volatility, even after accounting for firm fundamental volatility and other external factors influencing volatility.

The study conducted by GC (2008) in the Nepalese capital market failed to confirm the presence of the asymmetric effect of volatility. This lack of confirmation can be attributed to the methodology employed in the study. G.C. utilized the GARCH (1,1) model, failing to capture the asymmetric effect adequately. The conventional GARCH model analyzes the effects of squared error terms, giving equal weight to both positive and negative market events. This method fails to capture the differences in the market's response to positive and negative events.

Alberg et al. (2008) analyzed Tel Aviv Stock Exchange (TASE) indices utilizing diverse GARCH models. This study examined the aspects of market volatility, considering both mean returns and conditional variance. Symmetric models were scrutinized alongside innovative asymmetric GJR and APARCH models, focusing on asymmetric effects. The results highlighted the pivotal role of asymmetric GARCH models, particularly those incorporating fat-tailed densities, in enhancing the precision of measuring conditional variance. Notably, the eGARCH was proficient in capturing the asymmetric effects in comprehending the complexities of market behavior. Further, the study (Dangal & Gajurel, 2021) also confirmed the presence of a leverage effect on the return of the NEPSE Index.

Incorporating deterministic structural shifts is pivotal in accurately measuring volatility persistence and the leverage effect. These shifts, often stemming from significant economic, political, or regulatory events, introduce crucial nuances into market dynamics. Ignoring these shifts can lead to biased estimates of volatility persistence and the leverage effect. As noted in the study of Lamoureux and Lastrapes (1990), the estimate of persistence and leverage may be overstated when deterministic structural shifts are not considered. Several other studies (Abdennadher & Hellara, 2018; Assaf, 2016) confirmed the validity of biased estimates of volatility attributes in the absence of deterministic structural shifts. Results indicated that standard (G)ARCH models applied to series with sudden volatility changes indicated higher volatility persistence than actual. Ewing and Malik (2005) used this methodology to detect shifts in the volatility of stock returns in emerging markets and exchange rates, respectively, and concluded that volatility persistence is overestimated if these deterministic breakpoints are ignored. Hamilton and Susmel (1994) argues that a good model should account for structural or regime shifts. It was concluded that accounting for volatility shifts considerably reduces the volatility transmission and, in essence, removes the spillover effects. Failing to consider structural shifts may even lead to incorrect inference as studies have shown that the structural breaks in a series are misinterpreted as the presence of long memory in a series (Diebold & Inoue, 2001). A structural break in a series may instigate the slow decay in the autocorrelation, and it may be construed as the presence of long memory in a series (Granger & Hyung, 2004). Thus, assessing the role of the structural changes in the models that estimate the long memory is essential before the conclusions are drawn. Meanwhile, the study also noted that models incorporating occasional break performed marginally better, however, the empirical results suggested a possibility such that, at least, part of long memory may be caused by the presence of neglected breaks in the series. By integrating these structural breaks into the analysis, researchers can capture the true impact of market events on volatility patterns and asymmetric responses to news. This consideration is expected to enhance the robustness and ensure that the findings reflect the genuine complexities of market behavior. Therefore, acknowledging and incorporating deterministic structural shifts are fundamental in conducting a comprehensive assessment of volatility persistence and the leverage effect, providing valuable insights into volatility aspect of market.

Research Methodology

The data set consists of daily returns calculated based on NEPSE and thirteen sub-indices from 2003-07-17 to 2023-03-14 obtained from the Nepal Stock Exchange (NSE) repository. The data is analyzed with the help of open-source software R 4.3.0. R packages "auto.arima", "strucchange" and "rugarch" have been used for model fitting. Following is the list of indices used in this study.

Table 1

List of Indices

Index	Observation	Period
R_COMM	4525	2003-07-17 to 14-03-2023
R_DEV	4525	2003-07-17 to 14-03-2023
R_FINANCE	4525	2003-07-17 to 14-03-2023
R_HOTEL	4525	2003-07-17 to 14-03-2023
R_HYDRO	3597	2007-07-03 to 14-03-2023
R_INV	483	2021-02-25 to 14-03-2023
R_LIFE	4525	2003-07-17 to 14-03-2023
R_MANUF	4525	2003-07-17 to 14-03-2023
R_MICRO	1414	2017-01-11 to 14-03-2023
R_MUTUAL	634	2020-07-16 to 14-03-2023
R_NEPSE	4525	2003-07-17 to 14-03-2023
R_NONLIFE	1062	2018-07-17 to 14-03-2023
R_OTHER	4525	2003-07-17 to 14-03-2023
R_TRADING	4525	2003-07-17 to 14-03-2023

Asteriou and Hall (2021) suggested modeling both the mean and the variance simultaneously when it is suspected that the conditional variance is not constant. The residual of the best-fitted mean specification is fitted into the variance specification to further the diagnosis of volatility persistence and the leverage effect. For this purpose, general mean return (r_t) specification is formulated as;

$$r_t = \mu + \Sigma_{i=1}^{P}\delta_i r_{t-i} + \Sigma_{i=1}^{Q}\gamma_i e_{t-i} + e_t \quad | \quad e_t|\Omega_t = iid\ N(0, \sigma_t^2) \qquad (1)$$

Where, μ represents the constant mean return of the series, r_(t-i) represents the lagged return of p^th order, e_(t-i) represents the error term of q^th order. The variance of error term is expected to have independently and identically distributed with zero mean and σ_t^2 variance which is affected by the new information set at time t represented by Ω_t. The return is defined as;

$$r_t = \frac{I_t - I_{t-1}}{I_{t-1}} \quad (2)$$

where, I_t represents the index value of indices at time t. Since, the r_t is calculated as a first difference of subsequent index value, it constitutes the integrated series of order 1. Meanwhile, the best-fitted ARMA order is identified based on the Akaike Information Criteria (AIC), Bayesian Information Criterion (BIC) and Log-likelihood (LogLik).

This study incorporates asymmetric GARCH specifications, such as the GJR-GARCH model proposed by Glosten et al. (1993), the exponential GARCH (EGARCH) model introduced by Nelson (1991), and the APARCH model by Ding et al. (1993). These models address the need for restrictions to ensure the positivity of the conditional variance, as noted in ordinary GARCH model by Bollerslev (1986). These models can capture the nonlinear functions to model the conditional volatilities as well as asymmetric effect which cannot be captured by standard ARCH/GARCH specifications.

Concerning the GARCH order, the efficacy of GARCH (1,1) provides the parsimonious parametrization of the model as suggested by Bollerslev (1986). Their analysis revealed that none of the widely recognized volatility models exhibited a significant superiority over the GARCH (1,1) model when it came to forecasting exchange rate and stock market volatility. This study in line with Bollerslev specify GARCH order of (1,1) in all the volatility specification.

The Generalized Autoregressive Conditional Heteroskedastic (GARCH) specification

The GARCH (1,1) model specification is outlined as;

$$\sigma_t^2 = \omega + \beta_1 \sigma_{t-1}^2 + \alpha_1 e_{t-1}^2 \quad (3)$$

$$\beta_1 \geq 0; \alpha_1 \geq 0; \beta_1 + \alpha_1 \leq 1$$

Glosten, Jagannathan, and Runkle (1993) proposed the variant of GARCH model to capture the asymmetries in terms of negative and positive shocks. The model specification of GJR GARCH is as follows.

$$\sigma_t^2 = \omega + \beta_1 \sigma_{t-1}^2 + \theta_1 e_{t-1}^2 d_{t-1} + \ \alpha_1 e_{t-1}^2 \quad (4)$$

$$\beta_1 \geq 0; \alpha_1 \geq 0;\ \theta_1 \geq 0;\ \beta_1 + \alpha_1 + \theta_1 \leq 1$$

Where, d_(t-1) is the dummy variable which takes value 1 for e_(t-1)<0 and 0 otherwise. This differentiates the impact of goods news and bad news. The above model specification can be extended to the following two equations to further its understanding.

When $e_{t-1} > 0 \rightarrow \sigma_t^2 = \omega + \beta_1 \sigma_{t-1}^2 + \alpha_1 e_{t-1}^2$

While $e_{t-1} < 0 \rightarrow \sigma_t^2 = \omega + \beta_1 \sigma_{t-1}^2 + (\theta_1 + \alpha_1) e_{t-1}^2$

The presence of leverage effect indicates the asymmetric market reaction to "good news" vs "bad news" of equal magnitude. The persistence is indicated by the sum of $\beta_1+\theta_1+0.5\times\alpha_1$.

Exponential GARCH (EGARCH)

Nelson (1991) initially proposed the concept of exponential GARCH (EGARRCH). The model is specified as;

$$\ln(\sigma_t^2) = \omega + \beta_1 \ln(\sigma_{t-1}^2) + \alpha_1 \left| \left(\frac{e_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right) \right| + \theta_1 \frac{e_{t-1}}{\sqrt{\sigma_{t-1}^2}} \qquad (5)$$

It considers the log of variance in evaluating the leverage effect. This makes the leverage effect exponential rather than quadratic, which ensures that the estimates of conditional variance are always non-negative. The parameter capturing the leverage effect in above model is θ_1. For $\theta_1=0$ implies the absence of leverage effect. Meanwhile, $\theta_1<0$ implies the greater impact of negative shocks whereas, $\theta_1>0$ implies the greater impact of positive shocks in expected volatility. The persistence in volatility is indicated by GARCH parameter (β_1).

Asymmetric Power ARCH Model (APARCH)

Ding et al. (1993) proposed the Asymmetric Power ARCH model. The model is specified as;

$$\sigma_t^{\phi} = \omega + \beta_1 \sigma_{t-1}^{\phi} + \alpha_1 (|e_{t-1}| - \theta e_{t-1})^{\phi} \qquad (6)$$

The θ_1 indicates the leverage term. For β_1 parameter captures the effect of past conditional volatility. The persistence of the model is given by, $\beta_1+\alpha_1$ k_1 where k_1 is the expected value of the standardized residuals z_t under the Box-Cox transformation of the term which includes the leverage coefficient θ_1 (Ghalanos, 2022).

Selection of Best-Fitted Volatility Specification

Following the methodology proposed by Cappiello et al. (2006), an exhaustive model selection process was undertaken to determine the most appropriate volatility specification for each sub-index. The best-fit model was selected based on a comprehensive assessment of criteria that included Log-Likelihood, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). However, it is worth to note that there is no consensus on the superiority of one model over another (Kohonen, 2013).

Structural Break Tests: Bai and Perron's Test

The structural breaks are identified using the method developed by Bai and Perron (1998, 2003a, 2003b). This method offers distinct advantages due to its capacity to internally detect multiple structural shifts while also providing the means to account for heterogeneity and autocorrelation within the residuals.
The methodology assumes that there are m breakpoints where coefficients shift from one stable regression relationship to another one. The process will produce m+1 segments in which the regression coefficients are constant, and the model can be presented as;

$$y_i = x_i\beta_j + e_i \quad \left(i = i_{j-1} + 1, \dots, i_j, \qquad j = 1, \dots, m + 1\right) \qquad (7)$$

Where, j denotes the index of segment. The number of segments signified by i_j are usually estimated endogenously. The breakpoints are estimated as such the residual sum of squares (RSS) of the above equation is minimum. Bayes Information Criteria (BIC) and Akaike's Information Criterion (AIC) and Residual Sum of Squares (RSS) were used to select the optimal number of breaks.

Incorporating Structural Changes

The asymmetric GARCH specifications are re-estimated after considering structural breaks with the dummy variables in variance equation, which is set to 1 from the break date forward, zero otherwise. General formulation of asymmetric GARCH with dummy in variance is specified as;

$$\sigma_t^2 = \omega + \beta_1\sigma_{t-1}^2 + \theta_1 e_{t-1}^2 d_{t-1} + \Sigma_{i=1}^{5} d_{hi} D_{hi} + \alpha_1 e_{t-1}^2 \qquad (8)$$

$$\beta_1 \geq 0; \alpha_1 \geq 0;\ \theta_1 \geq 0;\ \beta_1 + \alpha_1 + \theta_1 \leq 1$$

The comparative change in log-likelihood values is used to evaluate model improvement due to the incorporation of such structural breaks. Based on the previous study (Abdennadher & Hellara, 2018), incorporating structural breaks is expected to improve the model fit of asymmetric GARCH.
The scope of this study is limited to diagnose the effect on estimated parameters of the volatility specification, with and without the consideration of deterministic structural shifts. It does not extend to forecasting the selected asymmetric GARCH specifications, leaving this as an area for future research to further validate and refine estimation of market volatility.

Empirical Results

The returns are calculated as relative percentage changes with a lag order of one. The incorporation of first differencing in the return calculations effectively mitigated the challenge of non-stationarity. Descriptive statistics of return of each of the subindices and composite NEPSE index is presented in Table 2.

Return series failed to confirm the normal distribution signified by the statistically significant Jarque-Bera Test statistics. Skewness statistics suggested a longer right tail and indicated large positive returns in the series data. High kurtosis values, prominently observed in indices such as "R_OTHER" and "R_LIFE," indicate fat tails in the distribution. It suggests a greater propensity for extreme returns, both positive and negative. The observed Fat-tailed distributions could be associated with heightened market volatility and uncertainty.

The ARCH effect is confirmed in the return series indicating the presence of autocorrelation in the return series. A statistically significant Augmented Dickey-Fuller coefficient indicates the absence of a unit root in the return data series for all indices. This implies that the return data series for each index is stationary, which is a fundamental assumption for time series analysis. Furthermore, statistically significant Ljung-Box Q coefficients were observed for all indices except for the Hotel and Mutual Fund Indices. The absence of the ARCH effect in these two indices post-transformation may be attributed to data transformation. These test statistics confirm the presence of the Autoregressive Conditional Heteroskedasticity (ARCH) effect, a prerequisite for volatility analysis. Consequently, the return series of the Hotel and Mutual Fund Indices were subjected to regression analysis with a constant mean ARMA (0,0) model.

Table 2

Descriptive Statistics Index Return

	Mean	Median	Std. Dev.	Skew	Kurtosis	ADF Test	Jarque-Bera	Ljung-Box Q	N
R_COMM	0.0005	-0.0004	0.0156	0.5106	8.88	-15.60**	6706***	259.39***	4523
R_DEV	0.0008	0.0000	0.0196	8.5146	461.60	-14.52**	39689599***	125.65***	4523
R_FINANCE	0.0006	0.0000	0.0156	2.8446	152.41	-13.46**	4213144***	11.36***	4523
R_HOTEL	0.0007	0.0000	0.0155	3.2822	61.44	-15.18**	651715***	1.74	4523
R_HYDRO	0.0005	-0.0008	0.0184	0.6577	6.38	-13.22**	1969***	110.44***	3595
R_INV	-0.0007	-0.0023	0.0208	0.7055	4.35	-7.49**	77***	5.82**	482
R_LIFE	0.0010	0.0000	0.0190	9.8035	496.36	-15.00**	45943742***	21.40***	4523
R_MANUF	0.0008	0.0000	0.0163	4.2486	201.60	-15.76**	7446824***	84.20***	4523
R_MICRO	0.0007	-0.0012	0.0174	0.6572	6.33	-9.08**	658***	18.79***	1230
R_MUTUAL	0.0005	0.0001	0.0103	1.2953	9.50	-7.75**	1291***	7.78	633
R_NEPSE	0.0006	0.0000	0.0127	0.3394	7.02	-14.73**	3131***	227.65***	4523
R_NONLIFE	0.0005	-0.0013	0.0191	0.6189	5.35	-8.07**	311***	9.81***	1061
R_OTHER	0.0012	0.0000	0.0373	30.6689	1421.28	-22.38**	380000000***	6.44**	4523
R_TRADING	0.0008	0.0000	0.0168	6.9291	186.81	-15.70**	6403524***	109.52***	4523

*** $p<0.001$, ** $p<0.01$, * $p<0.05$

Note: Augmented Dickey Fuller (ADF) Test measured the stationarity, Ljung Box Test measured the presence of autocorrelation, and Jarque Berra Test measured the normality of distribution of indices.

The standard deviation (Std. Dev.) is an important indicator of volatility in the return series. Indices such as "R_OTHER" and "R_INV" exhibit relatively higher standard deviations, signifying greater price variability. Conversely, indices like "R_MUTUAL" and "R_NEPSE" have lower standard deviations, indicating more stable returns.

Table 3 reports the identified best-fitted ARMA order. The optimum order is selected as such the value of information criteria, AIC, and BIC, are minimum and the maximum log likelihood ratio. The built-in script 'auto.arima' function, integrated within the R 4.3.0 software, is harnessed for assessing a multitude of best-fitted ARMA model combinations. The best fit ARMA order of Hotel and Mutual fund with the highest log-likelihood value is (0,2) and (1,1); however, due to statistically insignificant Ljung Box test of autocorrelation, the return series of these two indices are regressed with constant mean. Thus, the Log-likelihood value for these noted indices is not the highest when regressed with a constant.

Table 3

Empirical Result of Model Fit on Return Series

	AR	MA	AIC	BIC	LogLik
R_COMM	0	1	-25105.34	-25086.09	12555.67
R_DEV	3	1	-25224.63	-25186.13	12618.32
R_FINANCE	3	1	-24861.99	-24823.49	12436.99
R_HOTEL	0	0	-24850.75	-24837.91	12427.37
R_HYDRO	0	2	-18633.67	-18615.11	9319.84
R_INV	2	2	-2382.52	-2361.63	1196.26
R_LIFE	2	2	-23050.23	-23011.73	11531.12
R_MANUF	3	1	-24512.53	-24474.03	12262.27
R_MICRO	1	3	-6498.09	-6472.52	3254.05
R_MUTUAL	0	0	-4006.04	-3992.68	2006.02
R_NEPSE	0	2	-26945.93	-26920.27	13476.97
R_NONLIFE	1	3	-5423.21	-5398.37	2716.60
R_OTHER	0	1	-16924.76	-16905.51	8465.38
R_TRADING	1	2	-24221.584	-24189.5	12115.79

Note: AR represents autoregressive, and MA represents moving average. The ARIMA order has been selected based on optimal information criteria parameters AIC, BIC, and Log-Likelihood criteria.

Extensive model selection process in line with the method proposed by Abdennadher and Hellara (2018) is used to identify the best fitted asymmetric GARCH specification for each of the indices. For this purpose, each asymmetric volatility model is estimated using the Nepal Stock Exchange return data, the details of estimates is available upon request. The selection process is characterized by evaluating model fit criteria, including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Log-Likelihood. The model exhibiting the favorable AIC, BIC, and Log-Likelihood values have been identified as the optimal fit for the asymmetric volatility specification, outlined in final column of Table 4. This rigorous approach ensures robustness in modeling and enhances the credibility and depth of the subsequent analysis, contributing to a better understanding of volatility dynamics within the Nepal Stock Exchange. The estimates of Table 4 are outlined as follows;

Table 4

Asymmetric Model Specification Selection

	eGARCH			GJR GARCH			APARCH			Selected Model
	AIC	BIC	LogLik	AIC	BIC	LogLik	AIC	BIC	LogLik	
R_COMM	-5.9118	-5.9033	13376	-5.8882	-5.8797	13322	-5.9089	-5.8990	13370	eGARCH
R_DEV	-5.9156	-5.9028	13387	-5.8070	-5.7942	13142	-5.9392	-5.9251	13442	GJRGARCH
R_FINANCE	-6.6577	-6.6450	15065	-6.6497	-6.6370	15047	-6.2521	-6.2379	14140	eGARCH
R_HOTEL	-6.0520	-6.0449	13692	-6.1775	-6.1704	13975	-1.9585	-1.9500	4435	GJRGARCH
R_HYDRO	-5.4111	-5.3991	9734	-5.4070	-5.3950	9726	-5.4131	-5.3993	9738	APARCH
R_INV	-4.9597	-4.8817	1204	-4.9620	-4.8839	1205	-4.9589	-4.8723	1205	APARCH
R_LIFE	-6.1412	-6.1284	13897	-6.1279	-6.1151	13867	-6.1566	-6.1424	13933	APARCH
R_MANUF	-6.0328	-6.0200	13652	-6.2626	-6.2498	14172	-5.7811	-5.7669	13075	GJRGARCH
R_MICRO	-5.4721	-5.4346	3374	-5.4614	-5.4240	3368	-5.4708	-5.4292	3375	eGARCH
R_MUTUAL	-6.3795	-6.3303	2026	-6.3227	-6.2735	2008	-6.3744	-6.3181	2022	eGARCH
R_NEPSE	-6.3397	-6.3297	14344	-6.3251	-6.3152	14311	-6.3340	-6.3221	14331	eGARCH
R_NONLIFE	-5.2597	-5.2175	2799	-5.2597	-5.2176	2799	-5.2636	-5.2168	2802	APARCH
R_OTHER	-5.4797	-5.4712	12398	-5.7572	-5.7487	13026	-5.7225	-5.7126	12948	GJRGARCH
R_TRADING	-6.3387	-6.3273	14343	-6.1746	-6.1632	13972	-6.1755	-6.1627	13975	eGARCH

Note: The table outlines the extensive GARCH Models specification test. The standard GARCH (sGARCH) model was compared with the asymmetric E-GARCH, T-GARCH and APARCH models. The model selection is based on maximum log-likelihood and minimum of Akaike Information Criteria (AIC) and Bayes Information Criteria (BIC). The best model according to each criterion is highlighted in bold while the selected best fit GARCH model specification is reported in the column "Selected Model".

It is, however, essential to acknowledge the absence of a unanimous consensus regarding the superiority of one model over another, as noted by Kohonen (2013).

Table 5

ARMA (p,q) Best Fit Asymmetric GARCH Specification Results

	R_COMM	R_DEV	R_FINANCE	R_HOTEL	R_HYDRO	R_INV	R_LIFE	R_MANUF	R_MICRO	R_MUTUAL	R_NEPSE	R_NONLIFE	R_OTHER	R_TRADING
	eGARCH	GJRGARCH	eGARCH	GJRGARCH	APARCH	APARCH	APARCH	GJRGARCH	eGARCH	eGARCH	eGARCH	APARCH	GJRGARCH	eGARCH
μ	-0.0002	0.0053	-0.00300***	0.0001	0.0000	-0.0007	-0.0003	0.0001	0.0005	0.0004	0.00014**	0.0002	0.0000	0.0003
δ_1		0.8929	1.08493***			-0.9443***	1.3821***	0.8326***	0.74325***	-0.64543***		0.7395***		0.8757
δ_2		-0.1462	-0.16702***			-0.5710	-0.3841***	-0.0681***						
δ_3		0.1177	0.07145***					0.0089						
γ_1	0.27935***	-0.6930	-0.86925***		0.2042***	1.0830***	-1.2308***	-0.7204***	-0.59535***	0.74312***	0.28706***	-0.6392***	-0.0020	-0.8189
γ_2					-0.0001	0.5568	0.2389***		-0.16688**		0.0078	-0.1620***		-0.0312
γ_3									0.07906*			0.1411***		
ω	-1.6540***	0.0000	-0.4633**	0.0000	0.0018	0.0000	0.0002	0.0000***	-0.5481***	-1.7863**	-0.9882***	0.0015	0.0000	-0.3829
α_1	0.0269	0.0500	-0.1276	0.1360	0.2737***	0.0359	0.2052***	0.0671***	-0.0066	0.1144	0.0017	0.1406***	0.0776	0.0128
β_1	0.8037***	0.9000	0.9427***	0.8910***	0.6412***	0.8666	0.8290***	0.9301***	0.9313***	0.8049***	0.8877***	0.8172***	0.9219	0.9499
θ_1	0.6271***	0.0508	0.4870**	-0.0560	-0.0845	0.2719	-0.0149	-0.0039	0.3399***	0.2135*	0.5244***	-0.1575	-0.0036	0.1952
ϕ					1.0999***	3.3784	1.1220***					0.9795*		
Persistence	0.8037	NA	0.9427	0.9990	0.8613	NA	0.9944	0.9953	0.9313	0.8049	0.8877	0.9292	NA	NA
LogLik	13376	13142	15065	13975	9738	1205	13933	14172	3374	2026	14344	2802	13026	14343

Note: The table reports the re-estimated parameter of the models presented in Table 5 with dummy variables introduced in each of the breakpoints identified in Table 6. The table reports the re-estimated parameter for each of the selected best performing $\mathrm{ARMA(p,q)-GARCH}$ model based on Log-Likelihood considering deterministic structural shifts denoted by dummy variables d_1, d_2, d_3, d_4 *and* d_5 Mean Equation specification for across all the models $r_t = \mu + \Sigma_{i=1}^{P}\delta_i r_{t-i} + \Sigma_{i=1}^{Q}\gamma_i e_{t-i} + e_t$ where, N (0, σ_t^2). δ_i represents the lag of return series of i^{th} order and γ_i represents the lagged error terms of p^{th} order. While variance specification used follows;

EGARCH→ $\ln(\sigma_t^2) = \omega + \beta_1 \ln(\sigma_{t-1}^2) + \alpha_1 \left|\left(\frac{e_{t-1}}{\sqrt{\sigma_{t-1}^2}}\right)\right| + \theta_1 \frac{e_{t-1}}{\sqrt{\sigma_{t-1}^2}}$, GJR GARCH → $\sigma_t^2 = \omega + \beta_1\sigma_{t-1}^2 + \theta_1 e_{t-1}^2 d_{t-1} + \alpha_1 e_{t-1}^2$, APARCH → as $\sigma_t^{\phi} = \omega + \beta_1\sigma_{t-1}^{\phi} + \alpha_1(|e_{t-1}| - \theta e_{t-1})^{\phi}$.

The variance equation is represented as $\beta_1$and α_1 captures the GARCH and ARCH effect while θ_1 measures the leverage effect. The persistence is calculated as the $\alpha_1 + \beta_1 + 0.50 \times \theta_1$(GJR GARCH), β_1(eGARCH) and for APARCH $\beta_1 + \alpha_1 k_1$ where k_1 is the expected value of standardized residuals z_{t-1} under the Box-Cox transformation of the term which includes the leverage coefficient θ_1 (Ghalanos, 2022). While Log-Likelihood parameter represents the model fit statistics.

Table 5 summarizes estimated volatility parameters derived from the selected asymmetric specifications. It is worth highlighting that the concurrent estimation of mean and variance equations aligns with Engle's recommendation, particularly when there are indications of non-constant conditional variance (Demekas & Nerlich, 2020)

The result indicated that Development Bank, Other, and Trading Indices did not exhibit statistically significant parameters capable of capturing either volatility persistence or leverage. The row designated for "persistence" in the table presents NA (Not Applicable) values for those model specifications where the estimated parameters related to persistence are statistically non-significant.
Table 6 below outlines the identified structural shifts in each of indices. Optimal number of structural shifts are determined based on ideal number of breaks suggested by most of the selection test outlined in first row of the table. The corresponding break dates signifying the deterministic structural shifts is outlined in final row.

Table 6

Empirical Results of Bai and Perron's (1998, 2003) Test

Test	R_COMM	R_DEV	R_FINANCE	R_HOTEL	R_HYDRO	R_INV	R_LIFE
Sup FT(l+1/l)	4	5	4	5	4	4	4
SIC	5	5	4	5	4	4	4
LWZ	5	5	4	4	4	4	3
Break Dates	11/23/2006 10/29/2009 12/26/2012 12/29/2015 2/9/2020	2/25/2007 1/28/2010 1/15/2013 1/17/2016 2/9/2020	4/23/2007 4/05/2010 7/02/2014 2/09/2020	12/19/2007 3/03/2011 2/10/2014 3/21/2017 2/09/2020	11/08/2009 11/21/2013 2/28/2018 12/08/2020	6/15/2021 9/30/2021 5/02/2022 8/28/2022	12/24/2006 3/07/2013 3/10/2016 2/09/2020
Test	R_MANUF	R_MICRO	R_MUTUAL	R_NEPSE	R_NONLIFE	R_OTHER	R_TRADING
Sup FT(l+1/l)	4	4	4	4	5	3	2
SIC	4	4	5	5	5	4	2
LWZ	4	4	5	5	5	4	1
Break Dates	3/09/2008 8/06/2012 8/11/2015 2/09/2020	8/07/2018 1/16/2020 1/21/2021 4/28/2022	1/06/2021 5/30/2021 10/21/2021 5/12/2022 9/18/2022	12/13/2006 11/18/2009 12/27/2012 12/31/2015 2/09/2020	6/23/2019 2/16/2020 1/13/2021 9/08/2021 5/18/2022	11/14/2006 10/21/2009 9/20/2012 2/09/2020	4/27/2008 2/09/2020

Note: A maximum five number of breakpoints were allowed. The trimming parameter used was 0.15 with level of significance set to 0.05.

A minimum of two breaks are identified in the case of R_TRADING index while maximum of five breaks are allowed. A retrospective examination of events surrounding the identified break dates have revealed that the Nepalese capital market is particularly sensitive during elections, regulatory changes related to interest rates, foreign reserves, money supply, pandemics, and technological shifts in capital market development. This is consistent with some previous research, confirming the impact of broader macroeconomic and political events (Hashim & Mosallamy, 2020; Raddant & Kenett, 2021; Wong & Hooy, 2021).

Once the deterministic structural shifts are identified, the volatility specification is re-estimated with structural shift dummy in variance equation as presented in Table 7.

Table 7

Model Estimation ARMA (p,q) GARCH Models with Structural Breaks

	Return on Indices													
	COMM	DEV	FINANCE	HOTEL	HYDRO	INV	LIFE	MANUF	MICRO	MUTUAL	NEPSE	NONLIFE	OTHER	TRADING
	eGARCH	GJRGARCH	eGARCH	GJRGARCH	APARCH	APARCH	APARCH	GJRGARCH	eGARCH	eGARCH	eGARCH	APARCH	GJRGARCH	eGARCH
μ	-0.0001	-0.0017	-0.0002	0.000	0.000	-0.001	0.000*	0.000	0.000	0.001	0.000	0.000	0.000	0.004***
δ_1	0.2899***	0.872***	1.112***			-0.958***	0.667***	0.636***	0.750***	-0.609***		0.848***		0.998***
δ_2		-0.149***	-0.155***			-0.597***	0.214	-0.009*						
δ_3		0.114***	0.009*					0.000						
γ_1		-0.693***	-0.901***		0.192***	1.093***	-0.486***	-0.615***	-0.598***	0.716***	0.288***	-0.717***	-0.074***	-0.989***
γ_2					-0.011	0.586***	-0.286***		-0.166***		0.004	-0.207***		0.014***
γ_3									0.081***			0.145***		
ω	-2.386***	0.000	-1.474***	0.000	0.000***	0.000	0.000*	0.000	-0.779***	-1.991	-2.041***	0.000	0.000	-0.142***
α_1	0.036*	0.050***	-0.024	0.617***	0.258***	0.039***	0.159***	0.207***	0.002	0.145***	0.011	0.094***	0.082***	-0.027***
β_1	0.744***	0.901***	0.863***	0.532***	0.575***	0.865***	0.705***	0.367***	0.902***	0.785***	0.797***	0.849***	0.920***	0.972***
θ_1	0.609***	0.085***	0.458***	0.397***	-0.028	0.283*	-0.025	0.684***	0.330***	0.106	0.545***	0.056	0.061***	0.221***
ϕ					2.794***	3.166***	2.426***					2.495***		
d_1	0.414***	0.000	0.483***	0.000	0.000	0.000	0.000***	0.000	-0.067*	-0.040	0.319***	0.000	0.000	-0.029***
d_2	-0.144***	0.000	-0.482***	0.000	0.000	0.000	0.000***	0.000	0.075*	0.116	-0.106***	0.000	0.000	-0.025***
d_3	-0.059	0.000	0.186***	0.000	0.000	0.000	0.000	0.000	0.000	-0.105	0.013	0.000	0.000	
d_4	-0.150***	0.000	0.285***	0.000	0.000	0.000	0.000	0.000	0.009	0.147	-0.056*	0.000	0.000	
d_5	0.188***	0.000		0.000						-0.138	0.208***	0.000		
LogLik	13476	13294	15436	16359	9713	1205	14010	20307	3380	2032	14420	2797	13107	14055
Persistence	0.744	0.994	0.863	1.352	0.944	0.953	0.894	0.924	0.902	0.785	0.797	0.965	1.033	0.972

**** p<0.001, **p<0.01, *p<0.05*

Note: The table reports the re-estimated parameter of the models presented in Table 5 with dummy variables introduced in each of the breakpoints identified in Table 6. The table reports the re-estimated parameter for each of the selected best performing $\mathrm{ARMA(p,q)-GARCH}$ model based on Log-Likelihood considering deterministic structural shifts denoted by dummy variables d_1, d_2, d_3, d_4 *and* d_5 Mean Equation specification for across all the models $r_t = \mu + \Sigma_{i=1}^{P}\delta_i r_{t-i} + \Sigma_{i=1}^{Q}\gamma_i e_{t-i} + e_t$ where, N (0, σ_t^2). δ_i represents the lag of return series of i^{th} order and γ_i represents the lagged error terms of p^{th} order. While variance specification used follows;

EGARCH→ $\ln(\sigma_t^2) = \omega + \beta_1 \ln(\sigma_{t-1}^2) + \alpha_1 \left|\left(\frac{e_{t-1}}{\sqrt{\sigma_{t-1}^2}}\right)\right| + \theta_1 \frac{e_{t-1}}{\sqrt{\sigma_{t-1}^2}}$, GJR GARCH → $\sigma_t^2 = \omega + \beta_1\sigma_{t-1}^2 + \theta_1 e_{t-1}^2 d_{t-1} + \alpha_1 e_{t-1}^2$, APARCH → as $\sigma_t^{\phi} = \omega + \beta_1\sigma_{t-1}^{\phi} + \alpha_1(|e_{t-1}| - \theta e_{t-1})^{\phi}$.

The variance equation is represented as β_1 and α_1 captures the GARCH and ARCH effect while θ_1 measures the leverage effect. The persistence is calculated as the $\alpha_1 + \beta_1 + 0.50 \times \theta_1$(GJR GARCH), β_1(eGARCH) and for APARCH $\beta_1 + \alpha_1 k_1$ where k_1 is the expected value of standardized residuals z_{t-1} under the Box-Cox transformation of the term which includes the leverage coefficient θ_1 (Ghalanos, 2022). While Log-Likelihood parameter represents the model fit statistics.

When structural shifts are accounted for, a significant reduction in the unconditional variance (ω) is observed for several indices, specifically Commercial Bank, Finance, Hydro, Life Insurance, Microfinance, NEPSE, and Trading. In contrast, the unconditional variance for the remaining indices does not exhibit statistical significance. The presence of statistically significant dummy variables indicates a shift in the unconditional variances within distinct periods demarcated by structural shifts. The lagged volatility term (β_1) exhibits statistical significance across all indices, indicating the presence of conditional volatility. The concise effect of change in measure of persistence and leverage parameter is presented in Table 8 exhibiting the impact of incorporating deterministic structural shifts.

Table 8

Difference in Variance Parameters with and without Dummy

		Log Likelihood Statistics			Persistence		Leverage	
Indices	Specification	Without Structural Breaks	Without Structural Breaks	Δ	Without Structural Breaks	Without Structural Breaks	Without Structural Breaks	Without Structural Breaks
COMM	eGARCH	13376	13476	100	0.8037	0.7436591	0.6271***	0.609***
DEV	GJRGARCH	13142	13294	152	NA	0.9935	NA	0.085***
FINANCE	eGARCH	15065	15436	371	0.9427	0.8627544	0.4870**	0.458***
HOTEL	GJRGARCH	13975	16359	2384	0.891	1.34535	NA	0.397***
HYDRO	APARCH	9738	9713	-25	0.8613	0.9443425	NA	NA
INV	APARCH	1205	1205	0	NA	0.9526981	NA	0.283*
LIFE	APARCH	13933	14010	77	0.9944	0.8940008	NA	NA
MANUF	GJRGARCH	14172	20307	6135	0.9953	0.9242597	NA	0.684***
MICRO	eGARCH	3374	3380	6	0.9313	0.9022681	0.3399***	0.330***
MUTUAL	eGARCH	2026	2032	6	0.8049	0.7854263	0.2135*	NA
NEPSE	eGARCH	14344	14420	76	0.8877	0.7967197	0.5244***	0.545***
NONLIFE	APARCH	2802	2797	-5	0.9292	0.9654187	NA	NA
OTHER	GJRGARCH	13026	13107	81	NA	1.0328083	NA	0.061***
TRADING	eGARCH	14343	14055	-288	NA	0.9717563	NA	0.221***

Note: NA represents the absence of persistence in volatility as the parameters yielding the volatility is statistically not significant.

Incorporation of structural shifts improved model fit parameters in 10 of the 14 cases. However, a decrease in Log-likelihood parameters is noted for the Hydropower, Non-Life Insurance, and Trading indices. In the case of the Investment index, although the model fit parameter remained unchanged, the volatility parameters became statistically significant, addressing a previous deficiency observed when structural breaks were not considered.

In line with the effect suggested by the (Abdelzaher, 2021; Lamoureux & Lastrapes, 1990) volatility persistence has decreased in 7 cases; meanwhile, in three cases, the persistence values have become statistically significant, in comparison to the model without considering for structural shifts. Similar findings can be observed in the case of asymmetric effect. In 4 of the cases, the leverage parameter is downward adjusted, meanwhile, additional 4 indices showed the statistically significant asymmetric effect in the specification when deterministic shifts are incorporated in the model.

Except for the Hydropower, Hotel, and Non-Life Insurance indices, the analysis revealed an expected improvement in the persistence of volatility. The indices representing Commercial Banks, Finance Companies, Life Insurance, Manufacturing, Microfinance, Mutual Funds, and NEPSE exhibited a reduction in the persistence value. It implies that, in these cases, the persistence of volatility decreased when accounting for deterministic structural shifts. However, it is important to note that the Development Bank index, Investment Companies, Other, and Trading indices showed a statistically significant persistence estimate, which was not significant in the absence of structural shifts. The result aligns with the findings of prior research (Aggarwal et al., 1999; Fang et al., 2008; Hammoudeh & Li, 2008).

Moreover, the result revealed that the asymmetric volatility, signified by the parameter θ_1, exhibited statistical significance for 10 of the 14 indices. Observation showed that all the θ_1 coefficients were positive, implying that investors in these indices tend to react more strongly to "bad news" than "good news." This asymmetric response to new events is a notable characteristic of these segments of the Nepalese capital market. Consideration of deterministic shifts are not only able to provide the robust estimate, but also able to provide the better model specification by capturing the persistence and leverage effect, which would otherwise be absent without considering for such shifts.

Theoretical Implication

This research provides a meaningful contribution to understanding the Nepalese capital market from a volatility perspective. This research provides a robust approach by incorporating the deterministic structural breaks in estimating the parameter, which was largely ignored in the extant research in the context of Nepal. The findings suggested that the incorporation of deterministic structural breaks corrects for the overestimation of the volatility parameters. The findings of this research provide a new avenue for further research testing the reliability and validity of forecasts based on identified volatility models. For instance, high-frequency financial time-series data usually lacked normality with fat-tailed distribution; however, this study took a more relaxed assumption regarding normality. Alberg et al. (2008) indicated that overall estimation could be improved by using the asymmetric GARCH with fat-tailed densities for measuring conditional variances such as Student-t or skewed Student-t.

Practical Implication

The findings of this research hold significant practical implications for investment and risk management. Understanding the volatility attribute empowers investors to make more informed strategies for managing their risk. With insights into how volatility behaves across different indices, investors can make better decisions regarding asset allocation, diversification, and implementing hedging strategies. This enhanced ability to manage risk can lead to more resilient investment portfolios that are better equipped to withstand market fluctuations.

Furthermore, these research findings are not limited to investment; they are relevant for regulatory bodies and policymakers. Tracing the retrospective events causing the structural shifts may provide meaningful insights into evaluating the event's economic significance and the market's reaction. Policymakers can use these insights to devise more resiliant and robust policies that lead to more sustainable capital market practices.

Conclusion

This paper investigated the volatility within the return series of major indices within the Nepal Stock Exchange. The longitudinal research design encompasses a 20-year dataset of daily return series spanning from 2003 to 2023, with the primary objective of characterizing the volatility aspects exhibited by these indices. This investigation delves into two fundamental dimensions of volatility: persistence and the leverage effect.

Consistent with the findings by Lamoureux and Lastrapes (1990), this study's findings showed that, in several instances, if not all, the estimates of persistence parameters across 7 out of the 14 indices exhibit elevated persistence values. Further, the degree of asymmetric effect was also overstated in the absence of deterministic structural shifts. Moreover, the improvement in re-estimated volatility specification with structural shifts confirms the robustness of the models' power to estimate the persistence and leverage effect.

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