STRUCTURAL CHANGE AND DIAGNOSIS OF NEPALESE STOCK MARKET VOLATILITY

A Research dissertation submitted to

Kathmandu University School of Management

in partial fulfillment of the requirement for the

Degree of Master of Philosophy (MPhil) in Management

Bishal Shrestha

KU Registration Number: 024791-18

Kathmandu, Nepal
November 2023

DECLARATION

I, hereby, declare this dissertation entitled Structural Change and Diagnosis of Nepalese Stock Market Volatility embodies the original research work that I carried out in partial fulfillment of the requirement for the degree of Master of Philosophy (MPhil) in Management of Kathmandu University School of Management and that this dissertation has not been submitted for candidature for any other degree.

....

Bishal Shrestha

November, 2023

RECOMMENDATION

This is to certify that Mr. Bishal Shrestha has completed his research work on Structural Change and Diagnosis of Nepalese Stock Market Volatility under my supervision and that his dissertation embodies the result of his investigation conducted during the period he worked as an MPhil candidate at the Kathmandu University School of Management. The dissertation is of the standard expected of a candidate for the degree of MPhil in Management. It has been prepared in the prescribed format of the Kathmandu University School of Management. The dissertation is forwarded for evaluation.

Dissertation Advisory Committee

1. Chair   Professor Devi Prasad Bedari

November 2023

Kathmandu University
School of Management

RESEARCH COMMITTEE APPROVAL

We have conducted the viva-voce examination of the dissertation *Structural Change and Diagnosis of Nepalese Stock Market Volatility* by Bishal Shrestha. We have found the dissertation to be original work of the candidate and written according to the prescribed format of the School of Management. We approve the dissertation as the partial fulfilment of the requirements for the degree of Master of Philosophy (MPhil) in Management.

Evaluation Committee

1.	Prof. Dr. Devi Prasad Bedari	Chair, Research Committee
2.	Prof. Dr. Binod K. Shrestha	Member, Research Committee
3.	Prof. Dr. Mahendra Prasad Shrestha	Member, Research Committee
4.	Prof. Dr. Rajan Poudel	External Examiner

November 2023

Pinchhe Tole, Sasatanchha, Balkumari, Lalitpur, Nepal | +977 01 5186029, 5186091 | Fax: +977 01 5186414
info@kusom.edu.np | info@ku.edu.np | www.kusom.edu.np | GPO Box 6250, Kathmandu

ACKNOWLEDGEMENTS

I am highly indebted to Prof. Dr. Devi Prasad Bedari, Dean of the School of Management and supervisor, for the precious guidance and ideas he provided me with while drafting the proposal and dissertation. His guidance has helped me to acquire a proper perspective and clear insight into the process. Furthermore, I must thank Ashok Raj Pandey, Prof. Dr. Biswo Poudel, Prof. Dr Bijay KC, Ass. Prof. Arjun K Shrestha and Niranjan Phuyal for their valuable guidance through my MPhil journey. Finally, it could not have been possible without the continued support of my fellow researchers, Mr. Ajay Dhungana, and Ms. Sabina Tuladhar.

Lastly, I thank Kathmandu University School of Management (KUSOM) for providing valuable opportunities and a platform for submitting this dissertation for discussion and feedback. Finally, I take responsibility for the information and content presented in the thesis, including any errors and shortcomings, and expect valuable feedback from the reader for further improvements.

Bishal Shrestha November 2023

ABSTRACT

In modern finance, understanding the interplay between risk and return is fundamental. Traditionally seen as the average variability of returns, volatility has gained significance in investment decisions. However, the conventional view of volatility as a constant has given way to the concept of conditional volatility, acknowledging its time-dependent nature affected by various factors, including lagged conditional variance and information shocks.

This study diagnoses the impact of incorporating deterministic structural shifts while evaluating the persistence and leverage effect in the volatility of the Nepal Stock Exchange, which was largely underrepresented in extant empirical works.

A family of asymmetric GARCH specifications were used to diagnose persistence and leverage effect with and without deterministic structural shifts. The results confirmed the downward adjustment of volatility persistence and leverage effect when such deterministic structural shifts are incorporated in the specification.

Moreover, persistence and volatility effects facilitated inferences regarding the degree of market efficiency of the Nepal Stock Exchange, revealing a weak-form inefficiency.

TABLES OF CONTENT

LIST OF FIGURES

LIST OF TABLES

ABBREVIATION

AIC	Akaike's Information Criteria
AMH	Adaptive Market Hypothesis
APARCH	Asymmetric Power ARCH
ARCH	Autoregressive Conditional Heteroskedasticity
ARMA	Autoregressive Moving Average
BIC	Bayes Information Criteria
CASBA	Centralized Application Supported by Blocked Amount
eGARCH	Exponential General Autoregressive Conditional Heteroskėdasticity
EMH	Efficient Market Hypothesis
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GJR GARCH	Glosten-Jagannathan-Runkle GARCH
H-Q	Hannan-Quinn Information Criteria
IID	Identically and Independently Distributed
JB	Jarque Berra
NEPSE	Nepal Stock Exchange
NOTS	NEPSE Online Trading System
NRB	Nepal Rastra Bank
RSS	Residual Sum of Squares
RWH	Random Walk Hypothesis
SEBON	Securities Board of Nepal
TGARCH	Threshold GARCH

CHAPTER I

INTRODUCTION

Stock market volatility serves as an important metric in evaluating investment decisions. It is directly related to market uncertainty and affects the investment behavior of enterprises and individual investors. (Markowitz, 1952) and Sharpe (1964) undertook the earlier initiative to construct the relationship between risk and return. Markowitz suggested that an investor should consider individual investments in isolation and analyze how these investments interact and affect the overall risk and return of the investment assets. Following the same contention, Sharpe (1964) formalized the capital assets pricing model where a return was established as the function of systematic risk factor associated with the securities. The classical notion of risk often assumes that the variance is constant at different points in time. However, with the development of financial theories and increasing empirical studies, it was found that the notion of constant risk needs to be revisited (Bollerslev, 1986; Engle, 1982). An empirical study on the volatility of stock market return has attracted researchers over several decades and garnered systematic research efforts to characterize it in different market settings (Alberg et al., 2008; Assaf, 2016; Ewing & Malik, 2005; Hamilton & Susmel, 1994; Raddant & Kenett, 2021). It is a great challenge for investors to get a generalized maxim concerning volatility due to its intricate nature, which varies across different market settings. This intricate nature of volatility presents numerous avenues for further empirical research in characterizing volatility across different markets.

Extant studies have shown that the degree of stock market volatility was affected by broader factors, such as politics (Bechtel, 2009; Chavali et al., 2020), terrorism (Chesney et al., 2011), natural calamities (Ferreira & Karali, 2015), earnings announcements (Dangol & Bhandari, 2019; Syed & Bajwa, 2018), financial crisis and contagion (Aggarwal et al., 1999; Fang et al., 2019; Samarakoon, 2011). Although the impact of broader macroeconomic factors on variance was imminent, the degree and nature of impact was found to vary in intensity across different market settings. Campello (2007) research on the partisanship impact on stock markets' behavior surrounding the election period in a sample of 120 cases, including developed and less developed countries, reported that investors respond to the election in the same way in both categories, while the magnitude of response was found to be stronger in developing countries compared to that of less developed countries. The difference in magnitude and direction of effect also varied within and across the market. The study conducted by (He et al., 2020) noted that the market performance across transportation, mining, environment, electricity, and heating industries had sustained the adverse impact during the COVID-19 pandemic. In contrast, industries related to manufacturing, information technology, education, and healthcare were found to be resilient to the pandemic. These instances provide the rationale to undertake the systematic effort in deciphering the market-specific/index-specific volatility diagnosis.

Nepalese capital market is dominated by the banking and financial sectors, with a limited number of listed companies. Despite its relatively small size and limited number of scrips, the market has witnessed significant volatility over the past decade. The only organized stock exchange, Nepal Stock Exchange (NEPSE), witnessed a record high of 3199.03 on August 2021, retracting to as low as 1815.14 on 25 September 2022 with a change of 1383.80 (-43.25%) over the period one year. Figure 1 shows a glimpse into the volatility of NEPSE over the period of 2007 to

2022. The sustained increase in the NEPSE index from around 500 in late 2007 to as high as 3200 by mid-2021 witnessed varying volatility in the index-specific returns.

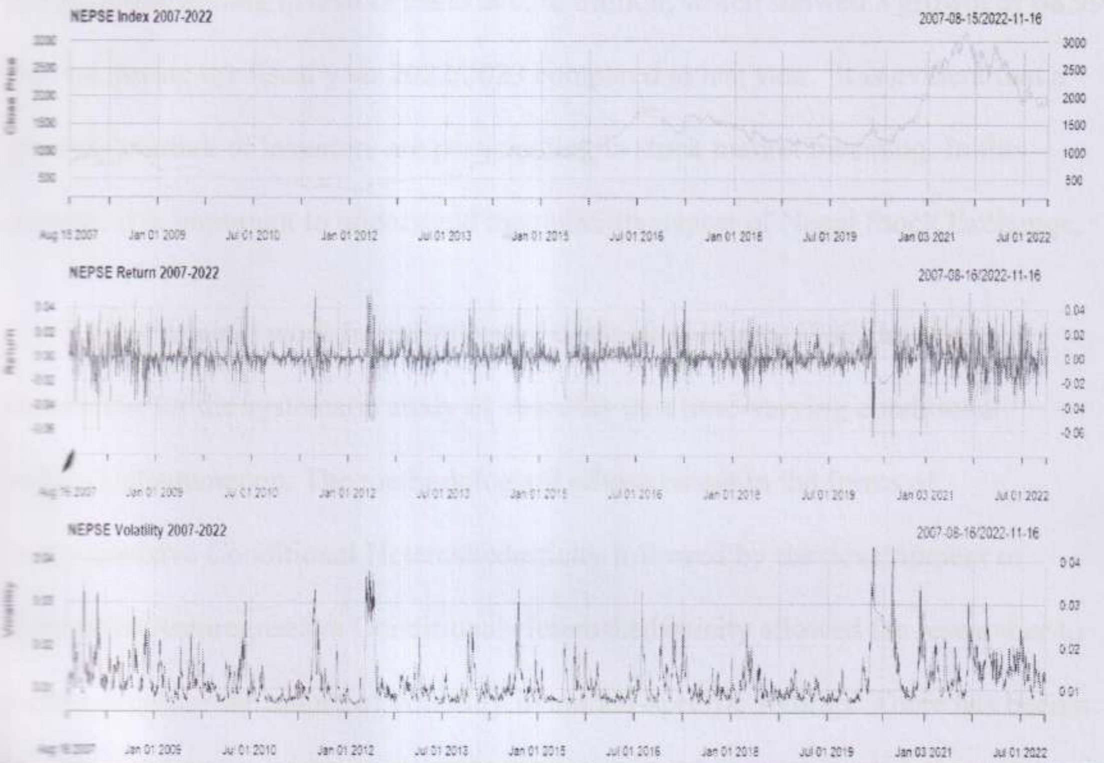


Figure 1. *NEPSE Index Daily Closing Price, Returns and Volatility 2007-2023*

The visual reference confirms the presence of volatility persistence and the cluster around specific periods. Understanding volatility clustering and its persistence provides an important insight into the market's reaction to notable socio-economic and political events. It provides the basis to evaluate the behavioral aspects of Nepalese investors concerning the events inducing the shocks in the return and its volatility.

Though in its early stage, the Nepalese capital market has grown significantly in the last decade. As of 09 November 2022, the Security Exchange Board of Nepal

(SEBON) report showed that more than 1.51 million investors are registered in the organized stock exchange of Nepal, with 1.04 million actively trading in the secondary market (Securities Exchange Board of Nepal, 2022). With the progressive transition towards digitizing stock trading in Nepal, the same report showed that the active online trading investors stand at 0.76 million, which showed a growth of 68.99 percent during the fiscal year 2022/2023 compared to last year. It is evident that a growing number of investors are participating in stock market investing. In this context, it is important to understand the volatility aspect of Nepal Stock Exchange.

The seminal work from Bollerslev (1986) and Engle (1982) laid the foundation for the systematic study of volatility as a time-varying conditional variance phenomenon. The methodological advancement in the forms of Autoregressive Conditional Heteroskedasticity followed by the development of Generalize Autoregressive Conditional Heteroskedasticity allowed the researcher to further diagnose the nature of volatility in market-specific settings. There has been a notable development in methodologies and tools since 1982 to diagnose volatility in the form of GJR GARCH (Bollerslev, 1987), EGARCH (Nelson, 1991), and APARCH (Ding et al., 1993). A significant restriction of the ARCH and GARCH specification is that they are symmetric. Because of the squared residual term, the symmetric volatility models would only consider the absolute effect of innovation without any information regarding the direction of change. Thus, the symmetric models cannot differentiate the effect on volatility from large positive or negative shocks of equal magnitude. However, financial time-series data, which are highly sensitive to broader political and macro-economic factors, showed that negative shocks (or 'bad news') in the market have a larger impact on volatility than positive shocks (or 'good news') of the same magnitude (Asteriou & Hall, 2021). GARCH-based analytical frameworks (EGARCH, GJTGARCH, APARCH) are able to capture the effect of nonsynchronous trading, conditional heteroscedasticity in returns, and asymmetric response to positive and negative news (Chau et al., 2014).

Followed by these notable studies in diagnosing the volatility aspect of market in international setting, several studies were accomplished in diagnosing the volatility attribute of the Nepalese capital market (Dangal & Gajurel, 2021; Dangol & Bhandari, 2019; GC, 2008; Rana, 2020). Despite broader examination of Nepal stock exchange from volatility perspective, these studies failed to account for deterministic structural breaks. The findings of Lamoureux and Lastrapes's (1990) study suggested that the failure to take into account of such deterministic structural shifts may cause the estimate of persistence to be overestimated. The identification of structural shifts was extensively studied by the work of Bai and Perron (1998, 2003a, 2003b) which further extended the rationale of considering for deterministic structural shifts in high-frequency financial time-series data, like that of stock price and return. Several further studies confirmed the effect in the persistence and leverage effect when deterministic structural shifts are considered for when diagnosing the volatility (Abdennadher & Hellara, 2018; Assaf, 2016; Tripathy & Alana, 2015).

Considering the empirical studies that underscore the significance of incorporating deterministic structural shifts when assessing volatility, this research is motivated to reevaluate the volatility persistence and the leverage effect within the Nepal Stock Exchange, a dimension notably underrepresented in prior research endeavors within the Nepalese context. Moreover, incorporating all thirteen sub-indices in conjunction with the NEPSE index enables this research to comprehensively understand index-specific characteristics related to volatility persistence and the leverage effect. The findings regarding persistence and leverage with deterministic structural shifts offer valuable insights for drawing inferences about the level of market efficiency within the Nepal Stock Exchange.

Problem Statement

Markowitz (1952) provided an early account of the significance of volatility in determining the optimum combination of expected return and variance in forming efficient portfolios. Despite its vital importance in forming the investors' expectations and affecting investment decisions, the concept of volatility is elusive and context dependent. Many studies (Bollerslev, 1987; Chau et al., 2014; Ding et al., 1993; Nelson, 1991) laid the foundation for systematically diagnosing time-varying conditional volatility. Understanding the attribute of volatility is important in the stock market as the decisions of the stock market participants are highly affected by the level of anticipated risk present in the market. Like any high-frequency financial time-series data, stock market price and return exhibit volatility clustering (Asteriou & Hall, 2021), which signifies high volatility followed by high volatility and low volatility followed by low volatility. The permanence of such a pattern of volatility clustering entails volatility persistence. Volatility persistence provides a unique insight into the market-specific volatility characteristics. Dangal and Gajurel (2021), in the study of the volatility of daily Nepal stock exchange (NEPSE) index return using the family of GARCH specification, noted that the conditional variance process is persistent. Similarly, the findings of Rana's (2020) study on the dynamics of time-varying volatility in stock returns indicated that volatility persistence was present in the daily return of the NEPSE index; however, it failed to confirm the leverage effect.

The noble effort of these previous studies was significant in diagnosing the volatility of the Nepal Stock Exchange. However, failing to consider deterministic structural shifts in volatility severely questions the unbiased property of estimated volatility parameters. Lamoureux and Lastrapes (1990) stated that the persistence in volatility may be overstated because of the existence of, and failure to account for, deterministic structural shifts in the model. To the researcher's knowledge, the deterministic structural shifts have not been considered while diagnosing the volatility in the Nepalese market setting. This research builds on this methodological gap and diagnose the persistence and leverage effect of conditional volatility of the Nepal Stock Exchange in the presence of deterministic structural shifts. The research findings help to assess whether the parameters of persistence and leverage effect are biased upward in the absence of deterministic structural breaks, as suggested by Lamoureux and Lastrapes.

Further, previous volatility studies, in the context of Nepal, were limited to use of the composite NEPSE Index. Given that the NEPSE index is an aggregate of thirteen subsectors in the Nepal Stock Exchange, the persistence and leverage effect would provide a meaningful attribution if evaluated at the sub-indices level. This study adds value as it extends the level of analysis by including all the major sub-indices along with the broader NEPSE Index, which provides a more in-depth understanding of volatility attributes at the sub-indices level.

The benefit of this study is two-fold; firstly, the analysis of volatility incorporating deterministic structural shifts provides an assessment of improvement in diagnosis of Nepalese capital market-specific volatility. Secondly, it provides the inference for the test of market efficiency considering the volatility aspect of the return series.

The noble effort of these previous studies was significant in diagnosing the volatility of the Nepal Stock Exchange. However, failing to consider deterministic structural shifts in volatility severely questions the unbiased property of estimated volatility parameters. Lamoureux and Lastrapes (1990) stated that the persistence in volatility may be overstated because of the existence of, and failure to account for, deterministic structural shifts in the model. To the researcher's knowledge, the deterministic structural shifts have not been considered while diagnosing the volatility in the Nepalese market setting. This research builds on this methodological gap and diagnose the persistence and leverage effect of conditional volatility of the Nepal Stock Exchange in the presence of deterministic structural shifts. The research findings help to assess whether the parameters of persistence and leverage effect are biased upward in the absence of deterministic structural breaks, as suggested by Lamoureux and Lastrapes.

Further, previous volatility studies, in the context of Nepal, were limited to use of the composite NEPSE Index. Given that the NEPSE index is an aggregate of thirteen subsectors in the Nepal Stock Exchange, the persistence and leverage effect would provide a meaningful attribution if evaluated at the sub-indices level. This study adds value as it extends the level of analysis by including all the major sub-indices along with the broader NEPSE Index, which provides a more in-depth understanding of volatility attributes at the sub-indices level.

The benefit of this study is two-fold; firstly, the analysis of volatility incorporating deterministic structural shifts provides an assessment of improvement in diagnosis of Nepalese capital market-specific volatility. Secondly, it provides the inference for the test of market efficiency considering the volatility aspect of the return series.

Several studies (Abdelzaher, 2021; Hashim & Mosallamy, 2020) in international market setting was used to test for market efficiency based on volatility attribute; however, not much of the research work in the Nepalese market setting considered volatility as a measure of market efficiency. Although, notable works of research delved into the test of market efficiency of the Nepalese capital market considering broader macroeconomic and political factors such as cash and stock dividend announcement effect (Dangol, 2016; Dangol & Bhandari, 2019), the effect of political events (Adhikari & Phuyal, 2016; Dangol, 2008), adaptive nature of market efficiency (Jha, 2019), this study uniquely contributes towards testing for market efficiency from the lens of volatility persistence and leverage effect with deterministic structural shifts.

Research Question

The continuum of the former problem statement provides a pretext to stipulate the measurable and objective research question. The heart of this empirical research lies in diagnosing the volatility aspect of the Nepalese stock market. This study addresses the key issue of considering deterministic structural shifts in diagnosing the persistence and leverage in Nepal Stock Exchange. In alignment with this research focus, the following research question serves as a guiding framework for this study.

Q1. How does incorporating deterministic structural shifts in measuring the persistence of volatility and the impact of leverage contribute to a more accurate diagnosis of volatility attributes and assess the stock market efficiency within the Nepal Stock Exchange (NSE)?

Research Objectives

The overarching research question has been subdivided into specific objectives to address each aspect individually. The following research objectives have been formulated to provide answers to the guiding research inquiry.

- To diagnose the impact of deterministic structural breaks in measuring the volatility persistence in the Nepal Stock Exchange.
- To diagnose the impact of deterministic structural breaks in measuring the leverage effect in the Nepal Stock Exchange.
- To evaluate the level of market efficiency in the Nepal Stock Exchange by considering the volatility persistence and leverage effect in the presence of deterministic structural breaks.

Significance of the Study

The research study is significant for understanding the Nepalese capital market and its volatility dimension, particularly the persistence and leverage aspects considering structural breaks. The research findings addressing the above research questions and objectives will meaningfully contribute to both academia and the practical realm of finance.

Understanding the extent of volatility persistence of the Nepal Stock Exchange will uncover the temporal volatility pattern. Understanding the persistence of volatility in the presence of structural shifts is crucial for investors and market participants as it allows them to anticipate and manage potential risks for given economic and noneconomic phenomena inducing such shifts.

Further, diagnosing the leverage effect in the Nepal Stock Exchange is crucial in understanding the essence of the asymmetric effect caused by market imperfections. Understanding the relationship between price movements and subsequent changes in volatility will shed light on how negative and positive price movements have differing impacts on volatility. The knowledge of the leverage effect after incorporating structural breaks provides important insight for market participants and regulators in identifying potential inefficiencies. It also provides insight into the behavioral aspect of market participants of the Nepalese capital market regarding the magnitude of reaction to negative and positive price movements. The findings will be helpful for market participants in designing the appropriate market interventions to enhance market efficiency.

Incorporating deterministic structural shifts in measuring volatility persistence and leverage effect addresses the critical methodological gap and potential bias in extant research conducted in the Nepalese market setting. By considering such structural shifts, this research will assess the accuracy of estimates and enhance the reliability of the findings, thus adding to the existing knowledge of the stock market volatility of the Nepal Stock Exchange.

The inference regarding the market efficiency of the Nepal Stock Exchange based on the volatility dimension provides a unique perspective to market participants. This renewed perspective helps market participants and policymakers gauge aspects, enabling them to devise policies and strategies accordingly.

Organization of the Study

This research paper is organized over five chapters. Chapter I included the pretext, introducing and problematizing the issue under study. Further, it outlines the guiding research question followed by research objectives to provide direction and objectivity outlined in understanding the volatility aspect of the Nepalese capital market. Chapter II extensively investigates the relevant literature concerning market efficiency, from the earliest notable seminal studies to the latest developments in behavioral finance. Works of literature are presented chronologically to understand better the progression of the competing schools of thought and ideas. The literature review section also incorporates the leading arguments and critical frames of discussions to preserve the discussion context and build up the arguments. Chapter III outlines the research methodology used for this empirical study. This chapter further delves into the specifics of sampling techniques, information regarding data collection, model specifications, and inherent constraints. In combination with Microsoft Excel, and data processing software R has been used to accomplish this research study. Chapter IV presents the results obtained using graphs and tables. It outlines descriptive statistics along with concerned statistical results from the model specification from Chapter III. Chapter V comprises a comprehensive discussion of results and findings with critical assimilation. The final section of the research is concluded with the summarized synthesis of all the significant characterization of stock return volatility in Nepal across major indices. Further, it provides the implication to existing and further research with due acknowledgement of major limitations inherited in this study.

CHAPTER II

LITERATURE REVIEW

This chapter discusses the relevant research works in the field of the stock market and its efficiency dynamics. Understanding market efficiency has always been an area of keen interest to investors and academicians. The estimation of the risk and return of securities in the market with a reasonable degree of confidence may assist investors in making a superior investment decision and increase the yield on their investment, which is greatly dependent on how well the stock market is able to reflect the available information in the prices of stock. However, the change in price of stocks is subject to numerous exogenous and indigenous factors, ranging from simple earnings announcements (Dangol & Bhandari, 2019; Syed & Bajwa, 2018) of the companies to the complex psychological and behavioral aspects (Kahneman & Tversky, 1979; Lo, 2004; Odean, 1998) of market participants. A review of all the literature in the field of the securities market and its behavioral aspects would be a formidable task. This section provides a comprehensive overview of literature related to stock market efficiency in conjunction with an in-depth review of stock return volatility dynamics and synthesizes prior studies to strengthen the groundwork for this study.

Empirical Reviews: Volatility Diagnosis

The foundation of volatility modelling lies in the Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models (Bollerslev, 1986; Bollerslev et al., 1994).

These models form the bedrock of understanding volatility patterns, capturing the inherent clustering of financial data.

In finance, the systematic study of volatility is a linchpin, weaving together various crucial facets of the financial domain. Its significance reverberates across investment strategies, risk management practices, market regulations, and decision-making processes. By delving into the patterns and intricacies of market volatility, investors gain a profound understanding of the inherent risks, enabling them to craft resilient portfolios and make informed investment choices. However, amidst its paramount importance, the diagnosis of volatility remains an intricate and elusive pursuit.

Before embarking on analyzing volatility attributes within the Nepal Stock Exchange, an exhaustive review of pivotal empirical studies investigating various facets of volatility serves as a crucial preamble. This comprehensive account of significant scholarly endeavors establishes the essential context and lays the groundwork for the subsequent exploration. By delving into these preceding research efforts, a nuanced understanding of the intricate dynamics of market volatility can be cultivated, offering a robust foundation upon which the present study builds its analytical framework.

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 indicated that NEPSE confirms the persistence of volatility in daily returns over the sample period. Dangal and Gajurel's (2021) study on volatility clustering in the NEPSE Index, using symmetric and asymmetric GARCH models, also revealed a positive link between volatility and the expected return of the NEPSE index in the form of risk premium, confirming the persistence in conditional variance. The growing body of research indicates a substantial focus on investigating volatility persistence in the Nepalese stock market. These efforts are driven by the market's expanding complexity and the increasing number of investors and policymakers engaging with it. Furthermore, these studies reflect a broader trend in the global financial research landscape, where emerging markets such as Nepal are gaining prominence due to their unique dynamics. The exploration of volatility persistence in the Nepalese context aligns with international research endeavors, fostering a comprehensive understanding of market behavior and contributing valuable insights to the broader field of finance.

The volatility persistence in financial time series also allows for inferences regarding the "memory property," which holds considerable significance within the realm of volatility analysis. Assaf (2016) examined the volatility attributes in MENA countries both before and after the 2008 financial crisis. The study's findings highlighted persistence in volatility, as evidenced by absolute and squared returns, whereas the returns exhibited a comparatively weaker indication of long memory.

Advancements in the capital market, especially in trading mechanisms, underscore the critical need for a systematic exploration of volatility. With the rise of high-frequency trading in the U.S. capital market, studies such as Zhang's (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. This underscores the significance of formulating trading strategies tailored to the expanding market to accommodate high-frequency trading. Furthermore, this accentuates the necessity for in-depth studies on the volatility of the

Nepalese stock market, particularly given its promising growth in terms of trading volume and frequency.

Another aspect of volatility that has garnered significant attention is an asymmetric effect, commonly referred to as the leverage effect. The leverage effect captures an asymmetry in volatility in response to 'good news' versus 'bad news'. The study conducted by GC (2008) in the Nepalese capital market did not establish 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 nuanced differences in the market's response to positive and negative events. These constraints of ARCH and the conventional GARCH model led to the development of methodologies capable of capturing the asymmetric characteristics inherent in volatility. Prominent among these are volatility specifications such as GJR GARCH (Glosten et al., 1993), eGARCH, and TGARCH (Nelson, 1991), as well as APARCH (Ding et al., 1993).

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 of Dangal and Gajurel (2021) also confirmed the presence of a leverage effect on the return of the NEPSE Index. Chan et al. (2015) showed that people hate to lose more than they like to win. Investor's common mistake of selling profitable stocks too soon and holding on to the unprofitable ones for too long (Odean, 1998). Related to loss aversion is the tendency of people to attach a higher value to an asset simply because it is in their possession, called the endowment effect. It shows the tendency of the stock market to show lower trading volumes when equity prices are declining and higher trading volumes when prices are rising. The phenomenon is clearly due to situational motivation. These unique observations of investment behavior delineate the importance of understanding leverage, which directly concerns the assessment of market efficiency.

Market efficiency, a cornerstone concept in finance, asserts that asset prices reflect all available information—however, the presence and understanding of the leverage effect challenge this notion. Asymmetric responses to positive and negative news can lead to exploitable market inefficiencies, where investors might gain disproportionate returns by strategically timing their trades based on the direction of news. Detecting and comprehending the leverage effect is crucial for regulators, investors, and financial analysts. Regulators are required to be aware of these asymmetries to design policies that ensure fair and transparent markets. For investors, recognizing the leverage effect can be the key to devising effective risk management and trading strategies, improving their ability to navigate volatile market conditions. Financial analysts, armed with knowledge about the leverage effect, can offer more accurate forecasts and recommendations, enhancing financial markets' overall efficiency and stability. Therefore, diagnosing the leverage effect is not only a theoretical pursuit but a practical necessity that significantly influences the functioning and perception of market efficiency.

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 & 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. Aggarwal et al. (1999) and 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. The Ljung-Box test for serial correlation is a useful diagnostic test for misspecification in the variance equation. Ewing and Malik conclude that accounting for volatility shifts considerably reduces the volatility transmission and, in essence, removes the spillover effects. Ignoring regime changes may significantly overestimate the degree of volatility transmission between the conditional variances of small and large firm returns. Failing to consider structural shifts may even lead to incorrect inference. Diebold and Inoue (2001) showed that the structural breaks in a series are misinterpreted as the presence of long memory in a series. Long memory in a series is represented by an autocorrelation that decays asymptotically and represents dependence on its past values. A structural break in a series may instigate the slow decay in the autocorrelation (Lamoureux & Lastrapes, 1990), 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, study of Granger and Hyung's study 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 analysis's precision 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 and accurate assessment of volatility persistence and the leverage effect, providing valuable insights into market efficiency and investor behavior.

Considering the deterministic structural shifts and their impact on persistence and asymmetry raises a unique concern about what kind of events led to such shifts in returns. Delving into existing research has unveiled various factors contributing to shifts in stock market volatility. The detailed examination of studies focusing on events causing such shifts in financial time series provides a foundation for delving into the broader literature encompassing various events that influence market dynamics and contribute to volatility fluctuations.

Macroeconomic and Political Factors Affecting Stock Market

Raddant and Kenett (2021) outlined that the global financial system is highly complex, with cross-border interconnection and interdependencies. This interconnectedness has resulted in the more propagated transmission of financial shocks and events into the global arena and might amplify into a global event. It analyzed the dependencies among 4,000 stock markets from 15 countries. The findings suggested that the energy, materials, and financial sectors are leading in connecting markets. This role has increased over time for the Energy and Materials sectors. The study concluded that the dependencies are rather volatile and that heterogeneity among stocks is a non-negligible aspect of this volatility. It also noted that the transmission mechanism between financial markets could have been more stable but governed by changing volatility and interdependence of stock contribution across countries.

Hashim and Mosallamy (2020), in a comparative study between the Egyptian and the US markets on the impact of presidential election outcome announcements on the stock market return and volatility, concluded that both markets efficiently absorbed the news and reflected it into stock prices and no statistically significant shifts in volatility were detected. It was an effort to provide a comparative understanding of different markets' behavior toward presidential outcome announcements. It has provided a glimpse of whether the markets at different economic development stages present similar efficiency in reacting to presidential elections.

Wong and Hooy (2021) studied the market response towards different types of politically connected firms during political events. The author noted that in emerging countries, it is a norm for firms to be politically connected. More often characterized by a weak legal framework, corporations exploit the system by investing in political rent-seeking. The study aimed to understand whether investors consider any value of the firms' political connection and, if so, which information might influence investors to bid up the firms' stock prices. The research result indicated that the market reacted more negatively towards government-linked companies and firms connected to family members of the government leaders than other politically connected firms. The author also presented that the stock market could have been more favorable towards firms connected through the close relationship between businesspersons and government leaders.

Kirana and Sembel (2019) study the effect of the presidential election on the stock market performance of the Indonesian stock exchange. The study set out to examine whether there was any abnormal return around the presidential election period, followed by an examination of whether abnormal return and trading volume activity significantly differed before and after the presidential election period. The research findings suggested no abnormal returns around the presidential election period and reported no differences in the average abnormal return before and after most events. Kirana reasoned that not finding a significant difference in abnormal returns during the election might be due to the irrelevance of information. Meanwhile, the result showed a significant difference in average trading volume activity before and after most of the events. Besides, the difference was found to be positive, as the analysis showed an increase in average trading volume activity after the event period of every event. This led to the conclusion that the presidential election positively affected the volume of stocks traded on the market around the event period.

Adhikari and Phuyal (2016) studied the influence of political events on stock market volatility in Nepal. The authors undertook a survey approach to identify the investors' and brokers' perceptions of the factors affecting the volatility of stock market return, followed by a multivariate analysis to test the significance of the factors identified in explaining the stock market volatility. Further, the authors attempted to trace the relationship between political instability and stock market volatility. The research result indicated that many investors and brokers identify political events as influencing factors in the share market. The authors indicated that they failed to establish a linear relationship between the role of usual economic variables on the variation of the NEPSE index. Meanwhile, the historical tracing of political events strongly influenced the share market volatility. Adhikari and Phuyal examined the effect of change in the prime minister on the average NEPSE index from 2003/4 to 2013/14. The researchers noted the average NEPSE index value five days before and after the commencement of the prime minister's term, along with an average of five days before and after the NEPSE Index value at the end of the term. The research was a simple descriptive analysis of the change of prime ministers. Nevertheless, the simple descriptive outlining of the events manifested few important observations. The study showed that the highest surge from 2003/04 to 2007/08 was noted with the increase in the NEPSE index by 295.79 points in the event of the signing of the comprehensive peace agreement. During that period, NEPSE reached its highest of 1175.38 points till 31st August 2008. It showed that anticipation of a positive political environment greatly increases market confidence and growth. Similarly, a decrease in the index was reported when an unstable political environment negated investors' expectation of a stable political scenario.

Nazir et al. (2014) investigated the relationship between uncertain political events and their positive, negative, or neutral impact on the stock market of the KSE-100 index using the major political events. Using the mean-adjusted return model and event study methodology, the authors concluded that the Karachi Stock Exchange was inefficient for a short period. It was reported that it usually took 15 days to reflect the effect of information on the prices of the securities. The authors pointed out that although political events do not have any direct relationship with stock markets, they are considered one of the main factors that may affect the stock market. It also stipulated that a stable political situation has a low systematic investment risk, encourages growth and capital investment, and improves the overall economy's performance.

Bechtel (2009) in his work examined the relationships between democratic politics and systematic investment (or capital) risk. Low risk was considered conducive to a well-functioning economy, facilitating capital investment, growth, and economic performance. The study distinguished pre-electoral, post-electoral and institutional factors and examined their influence on the systematic investment risk. The study results concluded that more favorable and reliable investment conditions during the incumbency of right-leaning government lead to lower investment risk. Meanwhile, the left-leaning government was associated with less favorable and higher investment risk. The grand coalition government, as well as periods of coalition formation, triggered the higher investment risk.

Białkowski et al. (2008) studied 27 OECD countries to examine the stock market volatility around national elections. It was noted that several factors, such as a narrow margin of victory, lack of compulsory voting laws, change in the government's political orientation, or the failure to form a government with a parliamentary majority, significantly contribute to the magnitude of election shock. Stock market participants reacted more volatilely during closely contested races, which were expected to result in a shift in the government's political orientation and when governments did not secure parliamentary majorities. In contrast, the compulsory voting laws led to reduced election shock. Researchers suggested that enacting such laws led to higher voter turnout, which improved the accuracy of pre-election surveys, reducing the volatility. The research findings concluded that markets with short trading histories reacted more strongly to the national elections. The stock prices reacted strongly in response to the unexpected result and were found to be temporarily elevating the level of observed volatility.

Beaulieu et al. (2006) investigated the short-run effect of the Quebec referendum on the return of the common stock of Quebec firms. The research findings suggested that political events had a statistically significant and positive impact on returns and trading volume of financial markets. The researchers argued that the uncertainty surrounding the expected result of the referendum and the fact that Quebec would remain within the Canadian federation probably yielded a positive impact. It was further argued that if the market participants had negatively conceived the referendum outcome, there would probably have been no reaction, given the large decrease in market level, when it became apparent that the referendum outcome could not be anticipated. The result indicated that the political uncertainty surrounding the major political events can have a short-run impact on the return of securities.

Önder and Şimga-Muğan (2006), studying how political and economic news affects emerging markets, suggested that the effect is reflected in the volatility of returns and trading volume in the emerging market in varying degrees. The result of the study suggested that both economic and political factors, as well as specific market characteristics, should be considered by investors when making an investment decision.

Bartov et al. (2000) provided a more detailed interpretation from the traders' perspective. After the quarterly earnings announcement, they observed the market inefficiency as manifested in the amount of drift in abnormal securities return. They suggested that the trading activity of unsophisticated investors was the main cause of the changes in stock returns after earning announcements. However, it was observed that institutional investors caused the continuation of the post-earnings announcement to drift after they had processed earning information appropriately. The paper argued that public news with clear information value implications will lead to lower trading Volume and smaller drift. They found that the high residual volume generated due to an earnings announcement implies a stronger drift, whereas low residual volume was associated with a weaker drift. The authors indicated that in the case of the positive earnings announcement, higher trading volume was observed after controlling for price changes and firm characteristics, suggesting a stronger drift. Meanwhile, in the case of negative news, the author found no systematic relationship between trading volume and subsequent returns, possibly due to additional noise like institutional arrangements such as constraints on a short sale.

Theoretical Review

Understanding market efficiency, even in its nominal form, is crucial for grasping the impact of volatility on stock market prices and returns. Theories surrounding market efficiency and the behavioral tendencies of market participants offer a conceptual framework for evaluating financial markets and comprehending how information is incorporated into asset prices. This conceptual understanding has a rich historical backdrop, dating back to the early 20th century. Notable contributors to this realm include Bachelier (1900), Cowles and Jones (1937), Kendall and Hill

(1953), and Working (1934), who laid the foundation for the concept of the Random Walk Hypothesis (RWH). The RWH posits that successive price changes in securities are independent and random. Early empirical validations of the RWH primarily focused on the statistical independence of securities prices, marking the test of the weak form of market efficiency. Over time, attention shifted to the impact of publicly available information on securities prices, reflecting the semi-strong form of market efficiency. Researchers like Richards (1975) delved into the market-making mechanisms, illustrating how efficient markets lead to prices converging with intrinsic values due to competitive investor interactions. This convergence occurs through rapid adjustments in response to new information, resulting in seemingly random successive price changes. These theoretical developments serve as a backdrop for understanding the intricate relationship between market efficiency, information assimilation, and the nuanced influence of volatility on financial markets.

Random Walk Hypothesis

The controversy surrounding determining securities prices, rooted in the Random Walk Hypothesis (RWH) proposed in the late 1950s, has been a focal point of financial research. The RWH asserts that successive changes in security prices are random, preventing investors from earning abnormal profits based on past behavior. Early empirical evidence supporting the RWH was presented by Roberts (1959) and Osborne (1959), highlighting the random characteristics of securities prices. Bachelier (1900) initially explored this concept of randomness, suggesting that speculation in French commodity markets resembled a "fair game," where price changes were equally likely to increase or decrease, implying unbiased future price estimates from present prices. Later studies, notably by Kendall and Hill (1953) and others (Cowles

& Jones, 1937; Fama, 1991; Fama et al., 1969; Mandelbrot, 1966), reinforced the independence and randomness of successive price changes in securities.

Theory and Development of Efficient Market

As the evidence supporting securities prices adhering to a random walk grew, the scholarly focus shifted towards elucidating the market-making processes underpinning this observed randomness. At the core of comprehending the seemingly stochastic nature of stock prices lies a profound understanding of market-making mechanisms. This systematic conceptualization and rigorous investigation of the market-making mechanism laid the foundation for formulating the Efficient Market Theory.

Samuelson's seminal work in 1965 demonstrated that current securities prices comprehensively incorporate all available information in an efficient market, leading to random price fluctuations. However, it became evident that this characterization only partially mirrors real market complexities. Subsequently, Fama et al. (1969) refined the conditions for market efficiency, asserting that information should be sufficiently accessible to investors, transaction costs must be reasonable, and asymmetry in investor information should not consistently yield abnormal profits. Richards (1975) emphasized that deeming a market efficient extends beyond price independence. While random securities pricing is a facet of market efficiency, the weak form of the Efficient Market Hypothesis (EMH) suggests that historical price sequences do not offer superior value for investment decisions or predict future prices.

Exploring further into understanding the Weak Form of Efficiency and the apparent randomness in securities prices, attention shifted to assessing market efficiency concerning the information derived from publicly available sources. This shift led to the Semi-Strong Form test development within the Efficient Market Hypothesis framework. The Semi-Strong Form tests are intricately concerned with evaluating the extent to which securities prices promptly incorporate publicly available information. The essence of the Semi-Strong Form Test lies in scrutinizing the swiftness with which information adjusts securities prices in response to new data. In a seminal study conducted in 1969, Fama et al. undertook a comprehensive investigation outlined in their pivotal paper, "The adjustment of stock prices to new information." Through this study, they sought to discern if there were distinct patterns in the rates of return on split securities in the months surrounding the split event and, if so, to what extent these patterns could be attributed to relationships between splits and changes in other fundamental variables.

Their research revealed that historical stock splits were frequently linked to significant dividend increases, creating a signaling effect wherein the split announcement indicated a growing stream of expected income from the shares. On average, the market's assessment of the information conveyed by a split was fully incorporated into share prices, typically by the end of the split month and often immediately after the announcement. Consequently, the study concluded that the stock market demonstrated efficiency, characterized by rapid adjustments of stock prices to new information. Interestingly, when considering the information impact of dividend changes, the apparent price effect of the split disappeared. It is indicated that the split influenced price adjustment only to the extent associated with the anticipated change in expected dividends. As a pioneering study in the semi-strong form test of market efficiency, the methods and outcomes of this research hold significant scholarly interest.

In an efficient market, securities prices are anticipated to reflect their "intrinsic value" based on all readily available information. Early advocates of market efficiency, such as Mandelbrot (1966) and Samuelson (1965), envisioned an idealized market scenario where information is freely accessible to all participants, and these participants share homogeneous expectations regarding the impact of current information on current prices and the future price distribution of each security. The intrinsic value of securities may fluctuate due to the introducing of new information. Rapid adjustments of prices to new information result in successive price changes that appear random. However, if new information is introduced gradually, successive price changes demonstrate dependence, weakening market efficiency.

In the study conducted by Scholes (1972) on the impact of large secondary offerings on securities prices, it was found that the subsequent fall in prices was not due to additional share pressure, indicating no correlation between block size and price decline. Instead, this price reduction was attributed to implicit information within the offerings. Scholes argued that in an efficient market, trades are influenced by available information, yet the market's competitive nature prevents any single piece of information from significantly affecting prices. Consequently, sales indicating possession of valuable information lead to share price drops, reflecting the expected value of the information. Similarly, buyers adjusting portfolios consider the seller's information value, affecting purchase prices. Large trades with higher information value are sold at reduced prices to account for the anticipated impact of the information. In another study by Ball and Brown (1968), examining the impact of annual earnings announcements on stock prices, it was observed that the market reacts congruently with deviations between expected and actual earnings, resulting in price declines for lower-than-expected earnings and vice versa. These findings align with the Efficient Market Hypothesis (EMH), which posits that individual investors form rational expectations, market information is efficiently aggregated, and equilibrium prices reflect all available information. Despite these principles, behavioral finance researchers challenge this assumption, contending that human behavior introduces systematic biases and deviations from rational decision-making, complicating the idealized efficiency of the market.

Behavioral Theories

Critics of the Efficient Market Hypothesis (EMH), notably Kahneman and Tversky (1979), have significantly challenged the conventional market depiction of efficiency due to the prevalence of behavioral biases among individual investors. These critics have underscored several inconsistencies about the foundational principles of utility theory upon which the classical EMH is built. The real market, they argue, exhibits investment behavior far more intricate than what is idealized by market efficiency theories. One compelling argument against the EMH comes from prospect theory, which elucidates the impact of behavioral biases on investors' decision-making. This theory highlights that individuals tend to undervalue probabilistic outcomes compared to certain outcomes. For instance, when presented with investment alternatives "A" and "B," where "A" offers a guaranteed payoff of $1000, while "B" promises a $3000 profit with a 50% probability and nothing with a 50% probability, test subjects consistently preferred the certain payoff of "A" over the probabilistic outcome of "B," despite the latter's higher expected payoff of $1500.

Similarly, in scenarios involving losses, individuals opt for probabilistic outcomes that involve a certain loss over those with a higher expected loss, showcasing a tendency known as the certainty effect. A study by Chau et al. (2014)

also revealed a noteworthy increase in the volatility of Islamic indices during political unrest. In contrast, these uprisings had little to no significant effect on volatility in conventional markets. This research indicates that market participants frequently exhibit predictable and financially detrimental behavior, if not outright irrational, challenging the assumptions of market efficiency.

Antony (2019), while characterizing the investors, it was evident that investors were interested in optimizing returns. The proponents of behavioral finance (Pasewark & Riley, 2010; Ricciardi & Simon, 2000; Thaler, 1999) argued that the process of optimization of investment decisions involved cognitive illusions. These cognitive biases cause asymmetry in market response.

Adaptive Market Hypothesis

The Adaptive Market Hypothesis (AMH), a relatively recent theory in financial markets, challenges the conventional belief that market participants are consistently rational and that markets operate efficiently. The AMH proposed by Andrew Lo in 2005 offers a comprehensive perspective on financial development. Unlike traditional theories like the Efficient Market Hypothesis (EMH), which assume rationality and perpetual market efficiency, the AMH acknowledges the impact of human behavior on financial markets. Numerous studies have revealed the inherent irrationality in human behavior and the occasional inefficiency of markets. The AMH recognizes these irrational tendencies and illustrates how such behavior can lead to market inefficiencies.

Moreover, the AMH provides a more realistic portrayal of financial markets. Unlike the EMH, which presupposes constant market equilibrium, the AMH appreciates the dynamic nature of financial markets. It recognizes that markets are in constant flux, with participants adapting to evolving conditions. Empirical evidence substantiates the AMH's viewpoint, indicating that markets frequently deviate from equilibrium, underscoring the hypothesis's validity (Lo, 2004).

Despite its attempt to reconcile the Efficient Market Hypothesis (EMH) with its behavioral critiques, the Adaptive Market Hypothesis (AMH) has faced criticism due to its challenge in producing consistent deductive tests of hypotheses. There needs to be more consensus among scholars regarding the appropriate methodologies for testing AMH. Additionally, the AMH posits that market participants are not always rational, a claim difficult to establish or refute conclusively. Another critique centers on AMH's broad and generic nature. While it aims to elucidate various financial phenomena such as market efficiency, bubbles, and crashes, the interconnections among these events and how the theory comprehensively explains them remain unclear.

In contrast to the classical EMH, the AMH acknowledges the occasional emergence of arbitrage opportunities (Lo, 2004, p. 24), citing the observations of Grossman and Stiglitz (1980). These opportunities are crucial as they incentivize information gathering, sustaining the essential aspect of price discovery in financial markets. Adopting an evolutionary standpoint, the existence of active liquid financial markets implies the presence of profit opportunities. As these opportunities are exploited and disappear, new ones continually arise due to the demise of certain market elements, the emergence of new entities, and changes in institutions and business conditions. Instead of the linear progression towards higher efficiency predicted by the EMH, the AMH suggests a significantly more intricate market dynamic. This complexity involves cycles, trends, and phenomena such as panics, manias, bubbles, and crashes, all commonly observed in natural market ecologies.

The analysis of market volatility serves as a critical link between the underlying theories of the Efficient Market Hypothesis (EMH), Prospect Theory, and the Adaptive Market Hypothesis (AMH). The framework of the EMH, which posits that all available information is already reflected in stock prices, is challenged by periods of significant volatility in the index returns. Volatile market behavior suggests that unforeseen events or human behavioral biases influence prices, deviating from the EMH's expectation of market efficiency. On the other hand, Prospect Theory illuminates the psychological factors at play during volatile periods. Investors tend to be risk-averse in gain situations but risk-seeking in loss situations, impacting their reactions to market fluctuations. Meanwhile, the AMH accommodates market volatility within its adaptive framework. It recognizes that markets are not always in equilibrium, allowing for the emergence of arbitrage opportunities and explaining the dynamic nature of market volatility. By integrating these theories, an in-depth understanding of market volatility emerges, revealing the intricate interplay between rationality, human behavior, and market adaptability in shaping financial markets.

CHAPTER III

RESEARCH METHODOLOGY

Research Design

This study uses a longitudinal research design. The daily sequential return and volatility dimension is measured over twenty years, from 2003 to 2023. The nature of the study requires us to investigate the temporal dimension of the volatility aspect of the Nepalese capital market to decipher time-varying volatility. This study takes a positivistic approach to evaluate the volatility using the various asymmetric models in the GARCH family, such as GJRGARCH, EGARCH, and APGARCH. Further, the breaks in volatility clusters are identified based on the approach suggested by Bai and Perron (2003b, 2003a).

Population and Sample

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. Following is the list of indices used in this study.

Table 1

List of Indices

Index	Observation	Period
NEPSE Index	4525	2003-07-17 to 14-03-2023
Commercial Bank Index	4525	2003-07-17 to 14-03-2023
Development Bank Index	4525	2003-07-17 to 14-03-2023
Finance Index	4525	2003-07-17 to 14-03-2023
Hotels Index	4525	2003-07-17 to 14-03-2023
Hydro Power Index	3597	2007-07-03 to 14-03-2023
Investment Index	483	2021-02-25 to 14-03-2023
Life Insurance Index	4525	2003-07-17 to 14-03-2023
Manufacturing Index	4525	2003-07-17 to 14-03-2023
Microfinance Index	1414	2017-01-11 to 14-03-2023
Mutual Fund	634	2020-07-16 to 14-03-2023
Non-Life Insurance	1062	2018-07-17 to 14-03-2023
Others Index	4525	2003-07-17 to 14-03-2023
Trading Index	4525	2003-07-17 to 14-03-2023

The Nepal Stock Exchange has been publishing the index data since February 12, 1994. This study, however, considers the period from 2003 to 2023 due to the availability and completeness of daily data. High-frequency daily data are better able to provide granular information and capture short-term fluctuations concerning the daily price movement. Including all the sub-indices and the NEPSE index in evaluating the volatility dynamics can provide a more comprehensive understanding of Nepalese capital market behavior and offer insights into specific sectors. The objective of this study is limited to the diagnosis of volatility from a macro perspective; hence, it does not include the analysis of data at the scrip level, which could limit the ability to provide the inference of volatility on individual stocks.

Research Hypotheses

The following research hypotheses are set out to provide inference based on the research questions.

H1: Volatility persistence in the Nepal Stock Exchange is biased upward in the absence of deterministic structural breaks. (Lamoureux & Lastrapes, 1990)

H2: The leverage effect in the Nepal Stock Exchange is biased upward in the absence of deterministic structural breaks. (Lamoureux & Lastrapes, 1990; Abdelzaher, 2021)

H3a: The measure of volatility persistence with structural breaks indicates the weak form of market inefficiency in the Nepal Stock Exchange.

H3b: The measure of leverage with structural breaks indicates the weak form of market inefficiency in the Nepal Stock Exchange.

From the graphical representation of returns in Figure 1, which pertains to the NEPSE Index as a whole, it is evident that there is a discernible pattern of conditional volatility. This pattern includes extended periods of low volatility followed by subsequent periods of both low and high volatility, thus indicating a cyclical nature in the volatility levels. The subsequent section delineates the specifications of the volatility modeling and its underlying intricacies employed in this study to assess the volatility characteristics within the Nepal Stock Exchange.

Model Specification

The time-series data exhibit characteristics such as volatility clustering and memory properties, where past innovations impact expected volatility positively or negatively. It is essential to consider specifications capable of capturing time-varying conditional volatility. Some notable models are the Autoregressive Conditional Heteroskedasticity (ARCH) model introduced by Robert F. Engle in 1982 and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model proposed by Bollerslev in 1987. These models, which consider lagged squared residuals and volatility, primarily capture the effect of information shocks, and lagged conditional volatility.

Volatility clustering, on the other hand, is a prevalent phenomenon observed in high-frequency daily stock return data. It is characterized by alternating periods of high and low volatility. The sequence of high volatility followed by high volatility and low volatility followed by low volatility, as documented by Asteriou and Hall (2021), is a distinctive feature signifying volatility persistence. The study of volatility persistence and the analysis of the differential impact of 'positive shocks' versus 'negative shocks' provide valuable insights into how market participants react to varying market conditions.

The applicability of ARCH specification is of limited use as it considers only the impact of past information shocks. GARCH specifications improvise to capture the effect of lagged conditional volatility and information shocks measured by squared error terms. However, the benefit of standard GARCH is limited to measuring the symmetric effect. Due to this limitation, various families of GARCH specifications capable of capturing the asymmetric effect are used to diagnose the volatility of the Nepal Stock Exchange. Specifically, three widely recognized models, namely GJRGARCH (Glosten et al., 1993), EGARCH (Nelson, 1991), and APARCH (Ding et al., 1993), are used to evaluate the asymmetric effect of volatility.

Engle's model suggested that the variance of the residuals at time t depends on squared error terms from the past periods. Engle suggested modeling both the mean and the variance simultaneously when it is suspected that the conditional variance is not constant (Asteriou & Hall, 2021, p. 311). The diagnosis of index return is based on the average daily price return, which is evaluated as follows:

$$r_t = \frac{I_t - I_{t-1}}{I_{t-1}}$$

Where, I_t represents the index value of indices at time t.

The Ljug-Box test statistic is used to test the serial correlation, signifying the ARCH effect in the series. Since the return series is calculated as the first difference of the subsequent index value, it constitutes the integrated series of order 1 [$I(1)$].

The GARCH framework uses the residuals from the best-fitted mean model. To determine the optimal AR(p) and MA(q) order, this study uses the R 4.3.0

"forecast" package "auto. arima" function in "R Software" to evaluate the ARMA order.

ARMA Model Specification

The following equation is regarded as a mean equation in GARCH framework;

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

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.

Standard GARCH Model

Previous research has demonstrated the efficacy of the GARCH (1,1) specification as a parsimoniously parametrized model (Bollerslev et al., 1994). The finding of the study by Hansen and Lunde in 2005 further reinforced this empirical finding. Their study rigorously tested the predictive performance of 300 different volatility models, comparing them to the GARCH (1,1) model. Surprisingly, 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. Therefore, this study uses the GARCH (1,1) parametrization for exploring both ARCH and GARCH effects.

$$r_t = \mu + \Sigma_{i=1}^{P} \delta_i r_{t-i} + \Sigma_{i=1}^{Q} \gamma_i e_{t-i} + e_t$$

$$e_t |\ \Omega_t = iid\ N(0, \sigma_t^2)$$

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

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

The model specifies that the volatility of the current period is affected by the lagged squared error term (acting as a new set of information) and lagged variance. The persistence is measured as the sum of β_1 *and* α_1. The standard GARCH considers only the absolute aspect of innovation signified by the squared lagged error term. Thus, the large positive shock (positive error term) will have a similar effect on expected volatility compared to that of large negative shocks (negative error term). However, for the financial time series data, it is expected that negative shocks ("bad news") in the market have a larger impact on volatility than do positive shocks ("good news") of the same magnitude as postulated by Prospect Theory (Kahneman & Tversky, 1979).

Therefore, the standard GARCH would be of limited use in diagnosing the stock market volatility characteristics in terms of studying the behavior of market participants. For this purpose, this study employs the variation of the GARCH framework, which is capable of accounting for asymmetric effects in volatility.

GJR GARCH

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.

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

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

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

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.

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

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

Thus, the sum of $\theta_1 + \alpha_1$ shows that the impact of bad news is higher by θ_1 compared to that of good news. For value statistically significant ($\theta_1 > 0$) coefficient implies the presence of leverage effect in evaluating volatility. 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;

$$r_t = \mu + \Sigma_{i=1}^{P} \delta_i r_{t-i} + \Sigma_{i=1}^{Q} \gamma_i e_{t-i} + e_t$$

$$e_t |\, \Omega_t = iid\ N(0, \sigma_t^2)$$

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

EGARCH also captures the asymmetric effect present in volatility. In EGARCH, 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. This model can well express fat tails, excess kurtosis, and leverage effects. The model specification used in this study is as follows;

$$r_t = \mu + \Sigma_{i=1}^{P} \delta_i r_{t-i} + \Sigma_{i=1}^{Q} \gamma_i e_{t-i} + e_t$$

$$e_t | \, \Omega_t = iid \; N(0, \sigma_t^2)$$

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

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).

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 Breaks

Bai and Perron (2003a, 2003b) have defined structural shifts as deterministic changes in the parameters or characteristics of a time series data-generating process. These shifts often manifest as abrupt and significant alterations in time series volatility, typically resulting from changes in external economic, financial, or social factors affecting the returns of financial assets.

It is noteworthy that previous research has underscored the potential overestimation of parameter estimates due to such structural shifts (Abdelzaher, 2021). Additionally, an analysis of daily stock-return data and a Monte Carlo Simulation experiment have lent empirical support to the hypothesis that GARCH measures of variance persistence can be highly sensitive to the misspecification of models caused by the omission of deterministic breaks (Lamoureux & Lastrapes, 1990). These findings underscore the importance of accounting for structural shifts in modeling and parameter estimation processes.

In the context of our analysis, structural breaks were identified using the method developed by Bai and Perron (1998, 2003a, 2003b). Subsequently, these identified structural breaks were incorporated into the analysis of volatility models. The 'strucchange' package built-in R 4.3.0 was employed to identify the deterministic structural shift processes suggested by Bai and Perron. This method offers distinct advantages, primarily 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;

$$y_i = x_i\beta_j + e_i \quad (i = i_{j-1} + 1, \ldots, i_j, \quad j = 1, \ldots, m+1)$$

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. The R documentation states that the algorithm for computing the optimal breakpoints given the number of breaks is based on a dynamic programming approach. The main computational effort is to compute a triangular RSS matrix, which gives the residual sum of squares for segment starting at observation i and ending at i' with $i < i'$.

Bayes Information Criteria (BIC), Akaike's Information Criterion (AIC) and Residual Sum of Squares (RSS) were used to select the optimal number of breaks. Caution was made in using the BIC, as it was found to choose a much higher value than the true one in the presence of serial correlation (Bai & Perron, 2003a). In addition to information criteria, the "sequential" method was used to validate further the optimal number of breaks, which was proven to be a more appropriate characterization for detecting the break in the study by Bai and Perron. Initially, breaks were estimated with $h = 0.15$ followed by referring to $supreme\ F\left(k + \frac{1}{k}\right)$ test performed to detect the presence of $(k + 1)$ breaks conditional on having k breaks. Based on the test statistics, the optimal breaks were identified for rejecting k breaks over $(k + 1)$ breaks. That implied the sum of k squared residuals, over all the segments, including an additional break, was sufficiently smaller than the square of the residual sum from the model with k breaks. The dates selected represent the boundary dates at which the breakpoints were identified.

Later, such structural shifts are retrospectively associated with the broader macroeconomic and political events surrounding the dates of identified structural shifts. It provides additional insight in characterizing the impact of broader macroeconomic and political events on leverage and the persistence of volatility in the capital market of Nepal. The results of this study enable us to infer the market efficiency of the Nepalese Stock Market. The study does not investigate further into the identified events surrounding the break dates and their nature of impact on volatility attributes.

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. The econometric specification of the mean and variance equation used is outlined as follows;

$$r_t = \mu + \Sigma_{i=1}^{P} \delta_i r_{t-i} + \Sigma_{i=1}^{Q} \gamma_i e_{t-i} + e_t$$

$$e_t | \, \Omega_t = iid \; N(0, \sigma_t^2)$$

General formulation of asymmetric GARCH with dummy in variance is specified as;

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

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

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.

Normality Test

The Jarque-Berra test is used to assess the normality of the financial time series. It can help determine if the residuals or errors of a financial time series model exhibit departure from normality. While evaluating the volatility specifications, the errors were assumed to be normally distributed, meanwhile, extant literature showed that results can be improved when error distribution addressing the fat-tailed data such as student-t distribution and standardized student t-distribution can be considered.

Stationarity Test

The Augmented Dickey-Fuller test is employed to examine the presence of a unit root, particularly in unadjusted index data, which is anticipated to exhibit non-stationary properties. Given that the modeling focuses on the return series of the respective indices, the application of the first differencing ratios is utilized to mitigate the issue of non-stationarity.

Autocorrelation Test

The Ljung-Box Q test, as introduced by Ljung and Box (1978), is applied to assess the presence of autocorrelation. This evaluation, performed on both unadjusted index and return series, confirms the presence of the Autoregressive Conditional Heteroskedasticity (ARCH) effect within the series. Following the fitted volatility model, the Ljung-Box test is subsequently utilized to appraise the appropriateness of the model's specification and to assess its goodness of fit. The absence of serial correlation in the residuals derived from the fitted volatility model indicates an optimal model fit and allows for the examination of any remaining autocorrelation within the series.

CHAPTER IV

RESULTS AND FINDINGS

A unit root persists across all the indices, as indicated by the statistically insignificant Augmented Dickey-Fuller coefficient. Moreover, the indices' data exhibit non-normal distribution characteristics, as evidenced by the divergent values of skewness and kurtosis and the Jarque-Bera Test statistics. Additionally, the Ljung-Box Test statistics reveal the presence of autocorrelation in all the indices.

The process of detecting and identifying structural breaks in the indices data followed the methodology proposed by Bai and Perron (2003a), selected for its capacity to account for heterogeneity and autocorrelation within the residuals. The study encompasses the period from July 18, 2003, to March 14, 2023, with a maximum daily observation count of 4524 for the NEPSE index and a minimum of 483 for the Investment sub-index. Detailed descriptive statistics for the NEPSE index and returns are presented in Table 2;

Table 2

Descriptive Statistics Index

Index	Mean	Std. Dev.	Skew	Kurt	ADF Test	Ljung Box Q	Jarque-Bera	N
Commercial Bank	836.98	482.79	0.52	2.28	-2.25	4517.47***	298.11***	4524
Development Bank	1182.10	1176.02	1.76	5.86	-2.11	4513.61***	3875.13***	4524
Finance	656.21	525.95	2.11	7.76	-2.12	4511.87***	7622.91***	4524
Hotel	1197.85	998.99	0.61	2.21	-2.29	4515.04***	402.52***	4524
Hydropower	1537.24	740.16	0.58	2.40	-3.30	3585.05***	252.44***	3596
Investment	82.10	18.05	0.20	1.82	-2.28	476.60***	31.25***	483
Life Insurance	4044.93	4656.17	1.29	3.96	-2.87	4518.85***	1425.33***	4524
Manufacturing	1655.31	1742.12	1.53	4.53	-2.50	4518.03***	2213.46***	4524
Microfinance	3062.88	1584.33	0.33	1.42	-2.36	1405.95***	150.79***	1231
Mutual Fund	13.95	1.83	-0.41	2.40	-0.67	626.33***	26.96***	634
NEPSE	975.52	692.17	1.08	3.55	-1.48	4517.94***	935.30***	4524
Non-Life Insurance	8422.02	3232.65	0.52	1.95	-1.36	1058.39***	96.55***	1062
Other	758.74	452.93	1.64	5.80	-2.32	4510.15***	3515.10***	4524
Trading	528.32	875.91	2.66	9.18	-1.80	4515.74***	12536.90***	4524

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

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.

Table 3 presents the descriptive statistics for the return series, which are computed using the index data. 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.

Table 3

Descriptive Statistics Index Return

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

The Jarque-Bera Test statistics indicate that the return data for all indices do not follow a normal distribution. This highlights the need to consider alternative distributional assumptions when modeling volatility. Skewness measures the asymmetry of the return distribution. As observed in some indices, positive skewness suggests a longer right tail and implies occasional large positive returns. Negative skewness indicates a longer left tail and the possibility of larger negative returns. 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.

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. These test statistics confirm the presence of the Autoregressive Conditional Heteroskedasticity (ARCH) effect, a prerequisite for volatility analysis.

Notably, the ARCH effect in the Hotel and Mutual Fund Indices was identified in the unadjusted data, characterized by coefficients of 3889.04 ($p < 0.001$) and 1077.88 ($p < 0.001$), respectively. However, this effect did not retain statistical significance when the data was transformed into a return series, employing differencing with a lag order 1. The absence of the ARCH effect in these two indices post-transformation may be attributed to data transformation. Consequently, the return series of the Hotel and Mutual Fund Indices were subjected to regression analysis with a constant mean ARMA (0,0) model. Furthermore, an assessment of the distribution of the return series indicated a departure from normality.

The determination of the optimal autoregressive (AR) order (p) and moving average (MA) order (q) is accomplished through the application of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Subsequently, the identified best-fit ARMA order is incorporated into the mean equation during the formulation of the model specification for asymmetric volatility models.

The 'auto.arima' function, integrated within the R 4.3.0 software, is harnessed for assessing a multitude of ARMA model combinations to identify the best-fit model specification. Table 4 comprehensively presents the ARMA (p, q) specifications that yield the lowest AIC and BIC values and the corresponding maximum Log-likelihood value.

Table 4

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.

Table 4 presents the results of the Autoregressive (AR) and Moving Average (MA) orders, along with the corresponding Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Log-Likelihood values for each index within the Nepal Stock Exchange (NSE). These model specifications capture the mean equation for subsequent volatility modeling. 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. Further, the Log-likelihood value is not the highest when regressed with a constant.

In financial time series analysis, the suitability of asymmetric GARCH models has been underscored by studies like Chau et al. (2014). These models are known for their ability to capture asymmetric volatility dynamics, overcoming the limitation of standard symmetric GARCH specifications. The current study focuses on GJR GARCH, eGARCH, and APARCH models among the array of asymmetric volatility models available. This study aims to determine the best-fitted asymmetric volatility model among GJR GARCH, eGARCH, and APARCH that accurately approximates the inherent volatility attributes within the Nepal Stock Exchange (NSE) return series. An exhaustive model selection process is undertaken to achieve the best-fitted models. For this purpose, each identified asymmetric volatility model is estimated using the Nepal Stock Exchange return data. 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 most favorable AIC, BIC, and Log-Likelihood values will be identified as the optimal fit for the asymmetric volatility specification. This rigorous approach ensures precision in modeling and enhances the credibility and depth of the subsequent analysis, contributing to a robust understanding of volatility dynamics within the Nepal Stock Exchange.

Table 5 presents a comprehensive overview of the estimated information criteria parameters and Log-Likelihood values for each asymmetric volatility specification considered in this study. In the specific case of the Development Bank Index, it is noteworthy that all the model-fit criteria indicated using standard GARCH specification as the best-fit model. However, it is essential to note that the primary objective of our analysis revolves around capturing the leverage and persistence effects inherent in the volatility series. However, the standard GARCH cannot capture the leverage effect. Thus, selecting the second-best model specification from among the available asymmetric volatility models for the Development Bank Index was decided. This judicious selection aligns with our objective of effectively modeling the leverage and persistence effects in the volatility series.

Notably, in most cases, all model fit parameters unequivocally indicated the adoption of asymmetric volatility specifications as the superior choice for modeling volatility dynamics. An exception emerges in three cases where the Akaike Information Criterion (AIC) indicates standard GARCH and another instance where the Bayesian Information Criterion (BIC) suggests standard GARCH as the preferred choice. To ensure clarity and ease of comparison, Table 5 comprehensively displays the information criteria values, including AIC, BIC, Hannan-Quinn (H-Q), and Log-Likelihood (LogLik).

The final column of Table 5 delineates the selected model for each index based on the outlined information criteria. This systematic model selection process aligns with the framework proposed by Abdennadher and Hellara (2018). 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). This rigorous approach to model selection enhances the precision and reliability of the analysis, ultimately contributing to a more robust understanding of volatility dynamics within the examined indices.

Table 5

Asymmetric Model Specification Selection

	eGARCH				GJR GARCH				APARCH				Selected Model
	AIC	BIC	H-Q	LogLik	AIC	BIC	H-Q	LogLik	AIC	BIC	H-Q	LogLik	
R_COMM	**-5.9118**	**-5.9033**	-5.9088	**13376**	-5.8882	-5.8797	-5.8852	13322	-5.9089	-5.8990	-5.9090	13370	eGARCH
R_DEV	-5.9156	-5.9028	-5.9111	13387	**-5.8070**	**-5.7942**	**-5.8025**	**13142**	-5.9392	-5.9251	-5.9342	13442	GJRGARCH
R_FINANCE	**-6.6577**	**-6.6450**	**-6.6532**	**15065**	-6.6497	-6.6370	-6.6452	15047	-6.2521	-6.2379	-6.2471	14140	eGARCH
R_HOTEL	-6.0520	-6.0449	-6.0495	13692	**-6.1775**	**-6.1704**	**-6.1750**	**13975**	-1.9585	-1.9500	-1.9555	4435	GJRGARCH
R_HYDRO	-5.4111	-5.3991	-5.4069	9734	-5.4070	-5.3950	-5.4027	9726	**-5.4131**	**-5.3993**	**-5.4081**	**9738**	APARCH
R_INV	-4.9597	-4.8817	-4.9290	1204	**-4.9620**	-4.8839	**-4.9313**	1205	-4.9589	-4.8723	-4.9249	**1205**	APARCH
R_LIFE	-6.1412	-6.1284	-6.1367	13897	-6.1279	-6.1151	-6.1234	13867	**-6.1566**	**-6.1424**	**-6.1516**	**13933**	APARCH
R_MANUF	-6.0328	-6.0200	-6.0283	13652	**-6.2626**	-6.2498	**-6.2581**	**14172**	-5.7811	-5.7669	-5.7761	13075	GJRGARCH
R_MICRO	**-5.4721**	**-5.4346**	**-5.4580**	3374	-5.4614	-5.4240	-5.4473	3368	-5.4708	-5.4292	-5.4551	3375	eGARCH
R_MUTUAL	**-6.3795**	**-6.3303**	**-6.3604**	**2026**	-6.3227	-6.2735	-6.3036	2008	-6.3744	-6.3181	-6.3526	2022	eGARCH
R_NEPSE	**-6.3397**	**-6.3297**	**-6.3362**	**14344**	-6.3251	-6.3152	-6.3216	14311	-6.3340	-6.3221	-6.3294	14331	eGARCH
R_NONLIFE	-5.2597	-5.2175	-5.2437	2799	-5.2597	-5.2176	-5.2438	2799	**-5.2636**	-5.2168	-5.2459	**2802**	APARCH
R_OTHER	-5.4797	-5.4712	-5.4767	12398	**-5.7572**	**-5.7487**	**-5.7542**	**13026**	-5.7225	-5.7126	-5.7190	12948	GJRGARCH
R_TRADING	**-6.3387**	**-6.3273**	**-6.3347**	**14343**	-6.1746	-6.1632	-6.1706	13972	-6.1755	-6.1627	-6.1710	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".

Figure 2 represents the estimated volatility of the NEPSE index under each of the four volatility specifications.

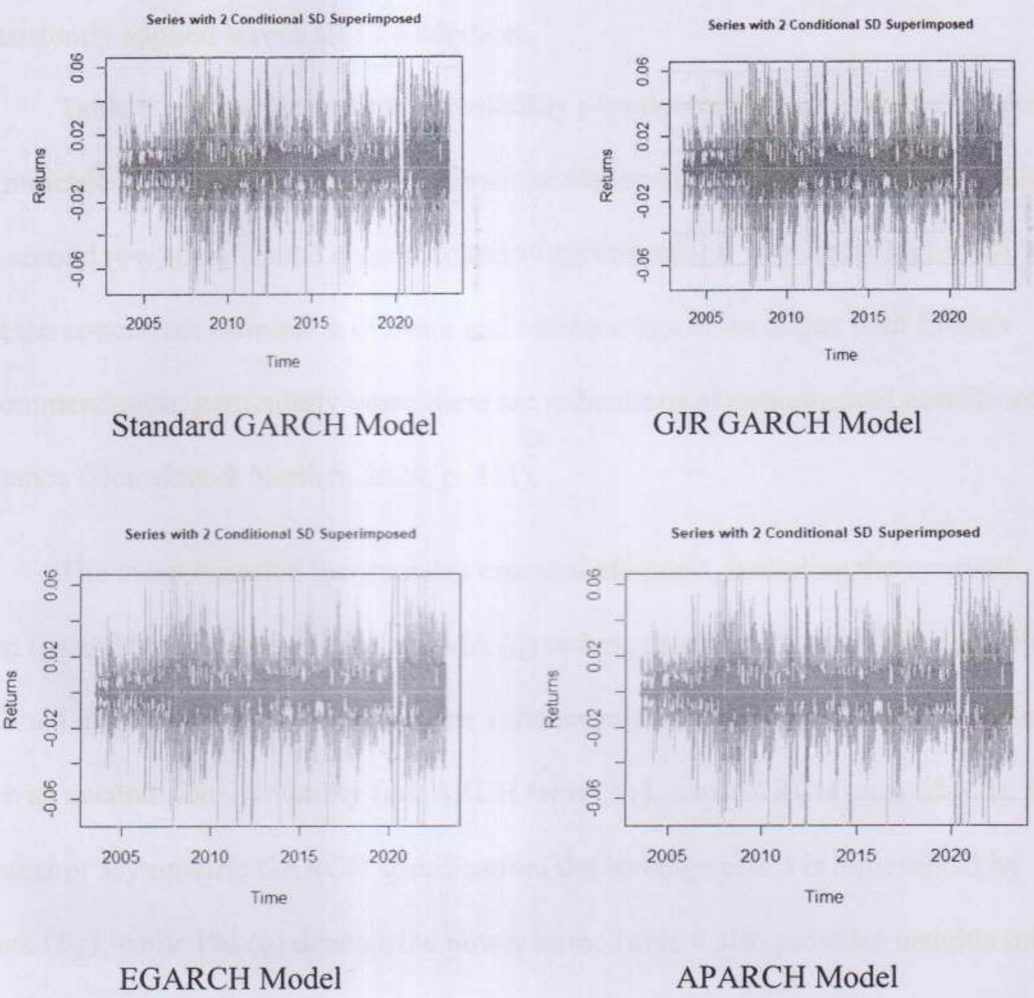


Figure 2. *Series with 2 Conditional SD Superimposed*

While informative, the visual representation of conditional standard deviation superimposed with the return series of the NEPSE Index in Figure 2 did not conclusively establish which model specification better represents the realized volatility series. However, upon referring to Table 5, a noteworthy observation emerges: the Log-Likelihood estimates for the eGARCH model (14344) exhibit improvement compared to those for the GJR GARCH (14311) and APARCH (14331) models.

Drawing upon this model-fit parameter, we have selected the asymmetric volatility estimate using the eGARCH specification to analyze the persistence and leverage effect of volatility within the NEPSE index. This selection process has been consistently applied across all 13 subindices.

Table 6 summarizes estimated volatility parameters derived from the selected asymmetric specifications. In the first row, the names of the indices are listed, while the second row specifies the chosen volatility 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, p. 311).

The mean equation incorporates essential elements, including the constant term (μ) and the selected AR (p) and MA (q) orders, determined through the criteria outlined in Table 4. Simultaneously, the variance equation comprises key parameters, such as unconditional volatility (ω), ARCH term (α_1), and GARCH term (β_1). In the context of asymmetric GARCH specification, the leverage effect is represented by Theta (θ_1), while Phi (ϕ) denotes the power term. Table 6 also provides insights into volatility persistence, leverage effect, and information criteria estimate for each selected volatility specification.

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

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

	Return on Indices													
	COMM	DEV	FINANCE	HOTEL	HYDRO	INV	LIFE	MANUF	MICRO	MUTUAL	NEPSE	NONLIFE	OTHER	TRADING
	eGARCH	GJR GARCH	eGARCH	GJR GARCH	APARCH	APARCH	APARCH	GJR GARCH	eGARCH	eGARCH	eGARCH	APARCH	GJR GARCH	eGARCH
μ	-0.0002	0.0053	-0.0030***	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	1.0849***			-0.9443***	1.3821***	0.8326***	0.74325***	-0.64543***		0.7395***		0.8757
δ_2		-0.1462	-0.1670***			-0.5710	-0.3841***	-0.0681***						
δ_3		0.1177	0.0714***					0.0089						
γ_1	0.2793***	-0.6930	-0.8692***		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	-1.654***	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	0.803***	0.9000	0.9427***	0.891***	0.6412***	0.8666	0.8290***	0.9301***	0.9313***	0.8049***	0.8877***	0.8172***	0.9219	0.9499
θ_1	0.627***	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

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

Note: The table reports the estimated parameter for each of the selected best performing ARMA(p, q) − GARCH model based on Log-Likelihood, the extended estimated parameters are reported in Annex Table 11 to Table 14. NA represents the absence of persistence in volatility as the parameters yielding the volatility is statistically not significant.

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, $N(0, \sigma_t^2)$. 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.

The parameter denoted as omega (ω) measures unconditional volatility inherent in the time series data. Among the 14 analyzed indices, six exhibit statistically significant levels of unconditional volatility. Notably, when assessed under the eGARCH model specification, the Finance Index displays the highest unconditional variance, recorded at 0.6392 [$e^{-0.4633}$]. In contrast, the Manufacturing Index, employing the GJRGARCH specification, demonstrates the lowest unconditional variance, approximately approaching zero.

Of particular interest is the observation that several indices, including the Commercial Bank, Finance, Microfinance, Mutual Fund, and NEPSE, exhibit negative omega values when analyzed within the eGARCH framework. Further, most of the indices employing GJR GARCH and APARCH specification resulted into statistically insignificant omega (ω) term whereas only one index in the case of eGARCH. This analysis sheds light on the diversity of unconditional volatility levels across different indices and offers valuable insights into the long-term volatility behavior in different indices in the absence of structural breaks.

In the analysis of 14 indices, it was observed that only four of them, namely Hydro, Life Insurance, Manufacturing, and Non-Life Insurance, exhibited statistically significant parameters for both ARCH (α_1) and GARCH (β_1). These findings imply that past information shocks and past conditional volatility play a substantial and statistically significant role in explaining the expected conditional volatility within the respective return series. It indicates that historical information shocks and conditional volatility are not random but possess meaningful explanatory power in forecasting future returns.

However, the relatively low number of indices displaying significant persistence may suggest that while some sectors or sub-indices exhibit noticeable patterns of volatility clustering, others may not conform to such behavior. It underscores the complexity and heterogeneity of financial markets, where different sectors may react differently to information shocks and structural shifts. It is interesting to explore further by considering deterministic structural shifts, which could enhance the market-wide volatility dynamics and provide more robust insights into the factors driving market behavior.

Of those indices showing statistically significant GARCH parameters, the higher degree of persistence in volatility can be attributed to the influence of past conditional volatility, as evidenced by the larger estimated values of the GARCH coefficients (β_1). This phenomenon aligns with the concept of volatility clustering, where periods of elevated volatility tend to be followed by subsequent periods of heightened volatility, while relatively calmer intervals succeed periods of lower volatility. These volatility clusters are of particular interest in the context of this research, as they serve as a basis for identifying deterministic structural shifts in volatility patterns throughout the series.

To visually illustrate these volatility clusters, Figure 3 has been provided, which delineates the volatility patterns in the NEPSE Index series from 2003 to 2023. The vertical lines in the figure denote the identified break dates, and it is noteworthy that a maximum of five breaks have been considered for this analysis. This visual representation aids in comprehending the clustering behavior of volatility in the NEPSE series over the specified time frame.

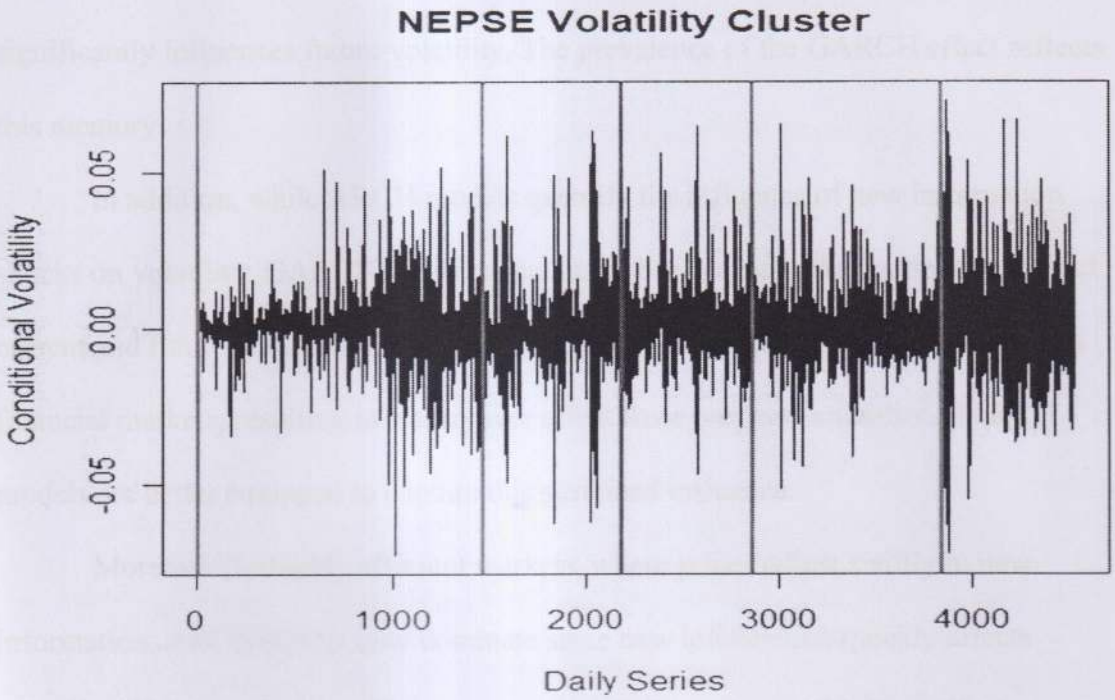


Figure 3 *NEPSE Volatility Clusters across the Break Dates*

When a greater degree of persistence in volatility is attributed to the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) effect as opposed to the ARCH (Autoregressive Conditional Heteroskedasticity) effect, it signifies that the volatility patterns in a time series data are predominantly influenced by past conditional volatility (GARCH) rather than by past information shocks (ARCH).

Volatility clustering is a common phenomenon in financial time series data, characterized by periods of high volatility followed by extended periods of high volatility, and similarly, periods of low volatility succeeded by prolonged periods of low volatility. The GARCH effect is well-suited to capture this characteristic as it emphasizes the persistence of past and present volatility patterns.

Furthermore, financial markets exhibit a form of memory whereby recent volatility conditions persist into the near future. If there is elevated volatility in recent periods, it is more likely to persist, and the same applies to low-volatility periods.

This concept aligns with the notion of "market memory," where past volatility significantly influences future volatility. The prevalence of the GARCH effect reflects this memory.

In addition, while ARCH models quantify the influence of new information shocks on volatility, GARCH models account for how past shocks continue to impact current and future volatility. Participants often respond to recent price movements in financial markets, resulting in a carryover effect from previous volatility. GARCH models are better equipped to capture this sustained influence.

Moreover, in highly efficient markets, where prices adjust swiftly to new information, ARCH effects may dominate since new information quickly affects volatility. However, in less efficient or more complex markets, GARCH effects can take precedence, as they capture the persistence of historical volatility patterns, even in the presence of new information.

Considering the research findings, the higher contribution of the GARCH effect to persistence suggests that recent information shocks do not solely shape current market volatility but are also influenced by the enduring patterns of past volatility. It indicates that market participants pay considerable attention to historical volatility trends, implying a certain level of market memory and suggesting that past volatility patterns remain relevant in contemporary market dynamics. It implies that investors are more concerned with adjusting their investment strategies based on past realized volatility instead of random information shocks.

The Theta parameter (θ_1) measured the asymmetric term (leverage effect) in GARCH specification. The Theta parameter (θ_1) in the GARCH specification measures the asymmetric term, commonly referred to as the "leverage effect." The results reveal that several indices, namely Commercial Banks, Finance, Microfinance, Mutual Funds, and NEPSE, exhibit statistically significant asymmetric terms in their volatility specifications. The finding underscores the presence of an asymmetry in the response to "good news" and "bad news" within these indices.

Specifically, the positive and statistically significant leverage parameter signifies that these indices display a heightened sensitivity to "bad news" relative to "good news." In other words, adverse developments or negative information have a more pronounced impact on these indices' volatility than positive developments or good news.

Figure 4 provides a visual reference to the leverage effect using the news impact curve of the NEPSE index. This visualization offers insights into how the index responds differently to positive and negative news, highlighting the pronounced impact of negative news on its volatility. It is important to note that this representation of the news impact curve is before accounting for deterministic structural breaks, emphasizing the significance of this asymmetry in the indices' volatility dynamics.

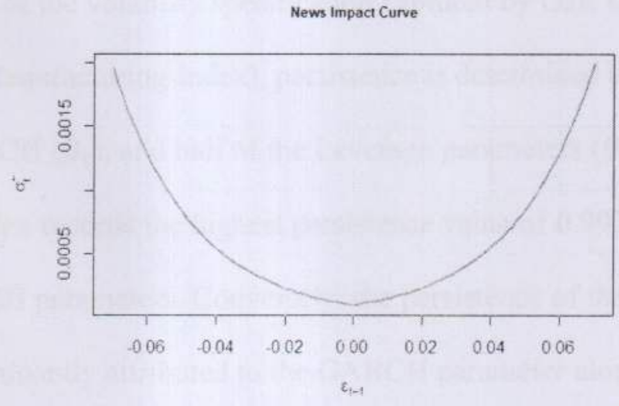


Figure 4 *News Impact Curve of NEPSE Index*

Upon visual inspection, one can discern a subtle difference in the impact of negative information shocks ($e_{t-1} < 0$) compared to positive information shocks ($e_{t-1} > 0$). While the news impact effect may not be distinctly pronounced in the graph, the presence of an asymmetric coefficient ($\theta_1^{NEPSE} = 0.5244, p < 0.0000$) confirms the differential impact of "good news" versus "bad news". This coefficient attests to the statistical significance of the dissimilarity in the influence exerted by positive and negative news on the NEPSE index's volatility, as indicated by the EGARCH model. The results indicated the similar readings can be observed across other indices with statistically significant leverage parameters.

The persistence in the expected conditional volatility involves the joint consideration of ARCH, GARCH, and Leverage effects. A higher value of the persistence parameter, closer to 1, indicates a greater dependency. When past information shocks and volatility significantly influence the expected conditional volatility, it implies a weak form of market inefficiency.

Examining the volatility specification represented by EGARCH (Commercial Bank, Finance, Micro Finance, Mutual Funds, and NEPSE), the β_1 parameter signifies persistence. The parameter ranges from a high of 0.9427 to a low of 0.8037. It suggests that a higher level of persistence stems from past volatility information.

In the case of the volatility specification captured by GJR GARCH (observed in the Hotel and Manufacturing Index), persistence is determined as the sum of ARCH (α_1), GARCH (β_1), and half of the Leverage parameters (θ_1). Notably, the Manufacturing index records the highest persistence value of 0.9972, primarily from ARCH and GARCH parameters. Conversely, the persistence of the Hotel index (0.8910) is predominantly attributed to the GARCH parameter alone.

Finally, for the volatility specification modeled with APARCH (of Hydro Power, Life Insurance, and Non-Life Insurance), persistence is assessed as the sum of GARCH and ARCH coefficients, adjusted with k_1, which represents the expected value of standardized residuals under the Box-Cox transformation of the term. It also includes the leverage coefficient θ_1. Across all the indices modeled with APARCH, it is observed that ARCH (α_1), GARCH (β_1), and the Power (ϕ) term significantly contribute to the persistence in volatility.

Prior research, including the work of Lamoureux and Lastrapes (1990), has shed light on the application of univariate GARCH models to financial data, revealing a notable degree of persistence in conditional variance. The prevalent high persistence in these models may be attributed to discrete structural breaks within the conditional variance series.

Except for the Commercial Bank, Hydropower, Mutual Fund, and NEPSE indices, the persistence coefficient for all other indices closely approaches 1. The observation underscores the necessity to explore the presence of volatility clustering by integrating deterministic structural shifts into the analysis. It becomes imperative to ascertain whether incorporating structural shifts impacts the measurement of the persistence parameter, a phenomenon highlighted in the research of Lamoureux and Lastrapes.

Table 7 provides the results of detecting deterministic structural breaks in the volatility series, employing the methodology prescribed by Bai and Perron (2003a, 2003b). The analysis incorporates three distinct statistical tests aimed at identifying these structural breaks.

The first row of the table presents the Supremum (Sup) F test statistics alongside the corresponding count of structural breaks identified when comparing the "$l + 1$" number of breaks against the "l" number of breaks.

Table 7

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

Test	COMM	DEV	FINANCE	HOTEL	HYDRO	INV	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	2/25/2007	4/23/2007	12/19/2007	11/08/2009	6/15/2021	12/24/2006
	10/29/2009	1/28/2010	4/05/2010	3/03/2011	11/21/2013	9/30/2021	3/07/2013
	12/26/2012	1/15/2013	7/02/2014	2/10/2014	2/28/2018	5/02/2022	3/10/2016
	12/29/2015	1/17/2016	2/09/2020	3/21/2017	12/08/2020	8/28/2022	2/09/2020
	2/9/2020	2/9/2020		2/09/2020			
Test	**MANUF**	**MICRO**	**MUTUAL**	**NEPSE**	**NONLIFE**	**OTHER**	**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	8/07/2018	1/06/2021	12/13/2006	6/23/2019	11/14/2006	4/27/2008
	8/06/2012	1/16/2020	5/30/2021	11/18/2009	2/16/2020	10/21/2009	2/09/2020
	8/11/2015	1/21/2021	10/21/2021	12/27/2012	1/13/2021	9/20/2012	
	2/09/2020	4/28/2022	5/12/2022	12/31/2015	9/08/2021	2/09/2020	
			9/18/2022	2/09/2020	5/18/2022		

Note: The optimal break selection methodology was based on Bai and Perron (2003a, 2003b). A maximum five number of breakpoints were allowed. The trimming parameter used was 0.15 with level of significance set to 0.05.

Global information criteria, namely the Schwarz criterion and the LWZ criterion, were employed to assess the optimal number of structural breaks, as detailed in the second and third rows of Table 7. These distinct methods yielded varying results regarding the ideal number of structural breaks. In this context, the number of structural breaks confirmed by any two methods was selected as an ideal number for categorizing the series data into clusters with differing levels of volatility. A maximum of five breaks were considered, with a trimming factor 15, and the significance level set at 5%. Of the 60 identified breakpoints, nine were on September 2, 2020.

The events surrounding the break dates were identified with major macroeconomic and political events. On March 24, 2020, a nationwide lockdown was initiated, suspending regular trading on the Nepal Stock Exchange (NEPSE) on March 22, 2020. Trading remained halted for 51 days, with the first resumption occurring on May 12, 2020. However, NEPSE's attempt to resume regular trading was short-lived, lasting only two days (May 12 and 13, 2020). Following a second trading halt, NEPSE resumed full operations on June 29, 2020, after a 48-day closure. This reopening witnessed a significant increase of 75.77 points, immediately followed by a decrease of 80.41 points on the subsequent trading day.

Over the subsequent 415 days, NEPSE experienced remarkable growth, reaching a high of 3198.60, representing an approximately 2.69-fold increase. This period marked the highest volatility in the history of NEPSE and was reflected in identifying a deterministic structural break in the return series of NEPSE indices.

Additionally, a subdued impact of COVID-19 was noted in the hydro sector, particularly in August 2020. Analyzing the historical data spanning the past five years, it becomes evident that the identified break dates coincide with significant macroeconomic and political events that influenced the stock market and the broader economy.

Significant developments in the capital market have led to substantial shifts in the volatility of various indices. Notably, the period from February to August 2018 witnessed the introduction of CASBA and the NEPSE Online Trading System (NOTS), marking a significant milestone in Nepal's capital market development as it transitioned toward an automated trading system. Additionally, events with political implications were found to have caused significant structural shifts in the indices. The dissolution of parliament on December 20, 2020, and May 22, 2021, resulted in notable structural shifts, with a substantial decline of 131.50 points observed in the first incident. Furthermore, announcing a populist budget in May 2021 during a transitional government period spurred a market growth of 166.20 points. In the weeks following this transition, NEPSE reached its highest point on August 18, 2023, reaching as high as 3199 points. However, on June 17, 2021, following significant growth in the NEPSE index, the Securities Exchange Board of Nepal (SEBON) published a list of 51 companies categorized as risky assets, leading to a substantial 52-point decline. Subsequently, due to pressures on foreign currency reserves and concerns regarding the speculative use of bank and financial institutions' lending in the stock market, the Nepal Rastra Bank (NRB) issued provisions limiting lending to four crore per bank and 12 crores in total per borrower through monetary policy on August 13, 2021, resulting in a 108-point index decline by September 4, 2021, with the structural shift date marked as September 8, 2021. NRB's regulations to restrict foreign currency reserve depletion and control growing interest rates included a circular issued on October 21, 2021, imposing a maximum 10% ceiling on interest rate changes. Structural shifts observed in April to May 2022 coincided with local-level elections. Furthermore, the dissolution of parliament on September 17, 2022, and the subsequently scheduled general election caused NEPSE to experience a structural break on September 18, 2022, resulting in a decline of 127.7 points by the end of the month. A timeline detailing significant broader macroeconomic and political events surrounding the break dates is presented in Figure 5.

Upon analyzing the break dates, it is observed that these events do not necessarily affect all indices simultaneously. For example, the first break in the Commercial Bank index occurred in November 2006, while the Development Bank index experienced its initial break two months later, and the Finance index followed four months afterwards. The pattern of breaks observed across the indices of banks and financial institutions suggests that the Commercial Bank indices tend to exhibit the initial deterministic structural break, followed by the Development Bank and Finance indices, with an average lag reaction of three months. It indicates a sectoral rotation of trading within Nepal Stock Exchange. The only identified breaks that had a widespread impact across most indices on the same date occurred on February 9, 2020, coinciding with the nationwide COVID-19 lockdown. The break dates of the Commercial Bank indices and the broader NEPSE index align closely.

This alignment can be attributed to the fact that a significant portion of NEPSE's market capitalization is represented by banks and financial institutions, primarily led by Commercial Banks. This observation affirms the prominence of sectoral rotation and investment shifts, although it does not conclusively establish a definitive sequence or pattern for such rotations or shifts. A careful examination of events coinciding with the identified structural break dates has 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. The scope of this study is limited to the diagnosis of the aggregate volatility attributes of univariate return series. The identified accounts of events surrounding the break dates are used to provide the validation to the breaks identified by the methods employed in this study.

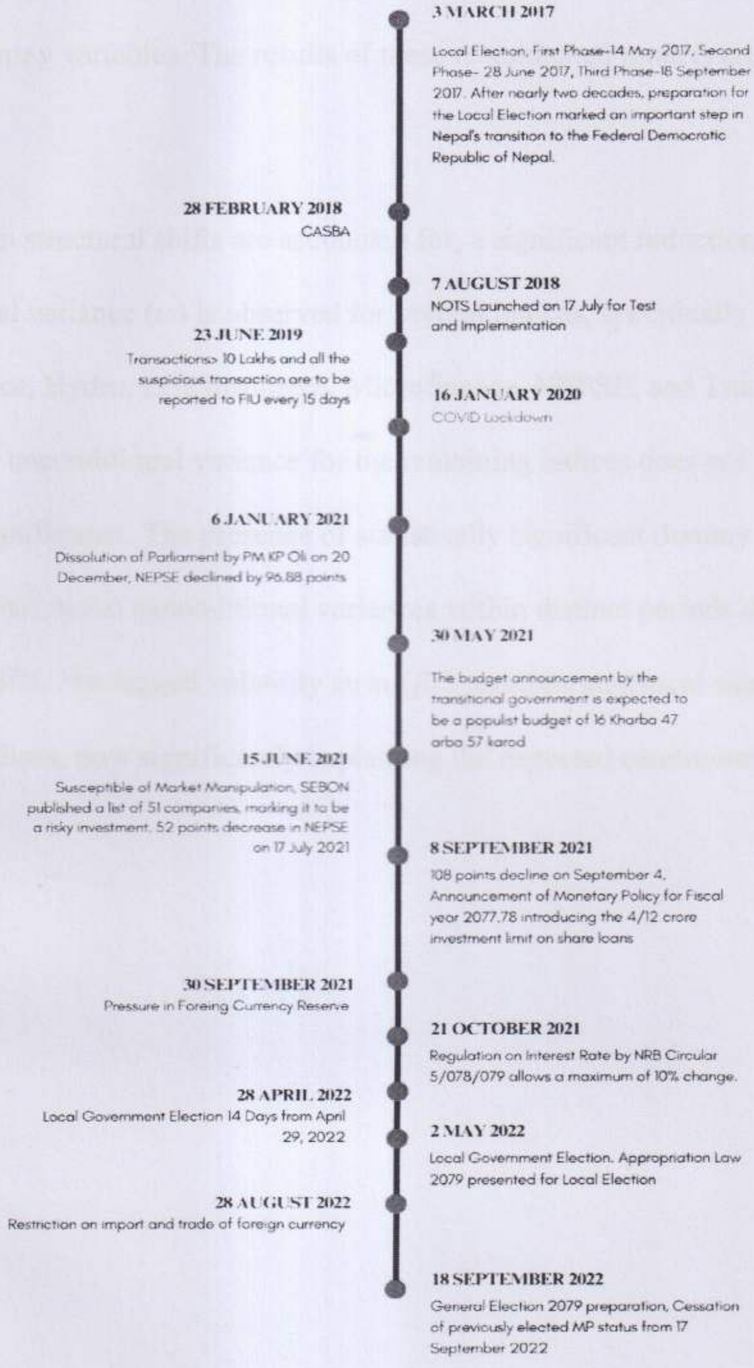


Figure 5 *Timeline of Macroeconomic, Political and Social Event Surrounding Break Dates*

Once these deterministic structural shifts have been identified, the suitable selected $ARMA(p,q) - GARCH(1,1)$ models are re-estimated, incorporating the relevant dummy variables. The results of these re-estimated models are outlined in Table 8.

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, now significantly explaining the expected conditional volatility.

Table 8

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	GJR GARCH	eGARCH	GJR GARCH	APARCH	APARCH	APARCH	GJR GARCH	eGARCH	eGARCH	eGARCH	APARCH	GJR GARCH	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 6 with dummy variables introduced in each of the breakpoints identified in Table 7. The table reports the re-estimated parameter for each of the selected best performing 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 $(0, \sigma_t^2)$. 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.

Similarly, the parameter representing the influence of lagged information shocks (α_1) demonstrates significant explanatory power in expected conditional volatility, except for Finance, Microfinance, and NEPSE indices. Moreover, significant leverage effects are observed in 10 of the 14 indices, in contrast to the previous scenario, where only five indices exhibited this behavior when structural shifts were not considered. These findings affirm that the influence of lagged information shocks, lagged conditional volatility, and news impacts become more pronounced when volatility specifications account for deterministic structural shifts.

Table 9 provides a concise overview of the comparative changes in estimates of persistence and leverage effect, accompanied by alterations in model fit parameters. When structural shifts are considered, 10 of the 14 indices observe improved model fit parameters. 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.

It is important to note that the persistence measures for the Hotel and Other indices exceed 1, which indicates spurious results, as a persistence value exceeding 1 suggests an explosive series. Furthermore, the volatility persistence values have decreased in 7 cases; meanwhile, in three cases, the persistence values have become statistically significant, in contrast to the scenario when structural shifts were not incorporated. The decrease in the persistence measure in most cases validates the findings of Lamoureux and Lastrapes (1990), which further establishes the rationale for this study. Apart from the downward adjustment of parameters, the statistical significance of parameters measuring volatility attributes showed statistical significance when deterministic shifts are considered.

Table 9

Difference in Variance Parameters with and without Dummy

Indices	Specification	Log Likelihood Statistics			Persistence		Leverage	
		Without Structural Breaks	With Structural Breaks		Without Structural Breaks	With Structural Breaks	Without Structural Breaks	With 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.

The results of the change in the volatility attribute of the Nepal Stock Exchange (NEPSE) and its constituent indices incorporating deterministic structural shifts have yielded several significant insights. One of the notable findings of introducing structural shifts is the increased responsiveness of the NEPSE and its subindices to recent information and shocks, signified by the decrease in the persistence parameters of most of the indices, if not for all.

Incorporating structural shifts often results in an improved fit of the volatility model to the data. This enhanced model fit is valuable for accurately capturing financial markets' complex and evolving nature. It can enhance risk assessment, forecasting accuracy, and the development of effective trading strategies.

The increased significance of volatility parameters underscores the importance of robust risk management practices. Investors should exercise heightened vigilance during periods of structural shifts, as market dynamics can evolve rapidly and unpredictably.

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 insignificant in the absence of structural shifts. The result aligns with the findings of prior research conducted by Aggarwal et al. (1999), W. Fang et al. (2008), and Hammoudeh and 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 news events is a notable characteristic of these segments of the Nepalese capital market.

Figure 6 shows the graphical representation of the news impact curve of the NEPSE Index considering deterministic structural breaks. It highlights the pronounced sensitivity of investors to negative news events, contributing to the asymmetric volatility patterns observed in the analysis. Furthermore, the investigation identified six additional statistically significant leverage parameters in indices when structural breaks were considered. Notably, these six indices showed the absence of leverage effect when structure breaks were not considered.

The findings implied that the leverage effect is multifaceted. On the one hand, the increased sensitivity to negative news events suggests that investors in these indices may adopt a more risk-averse stance when confronted with adverse information, potentially resulting in sharper market reactions. The heightened responsiveness to "bad news" could influence these segments' trading behaviors, market sentiment, and overall market dynamics.

In addition to that, the presence of statistically significant leverage parameters in more indices when structural breaks are considered may reflect a greater degree of heterogeneity in market responses to news events. This increased variation in market reactions could lead to divergent price movements and trading patterns across different segments of the Nepalese capital market.

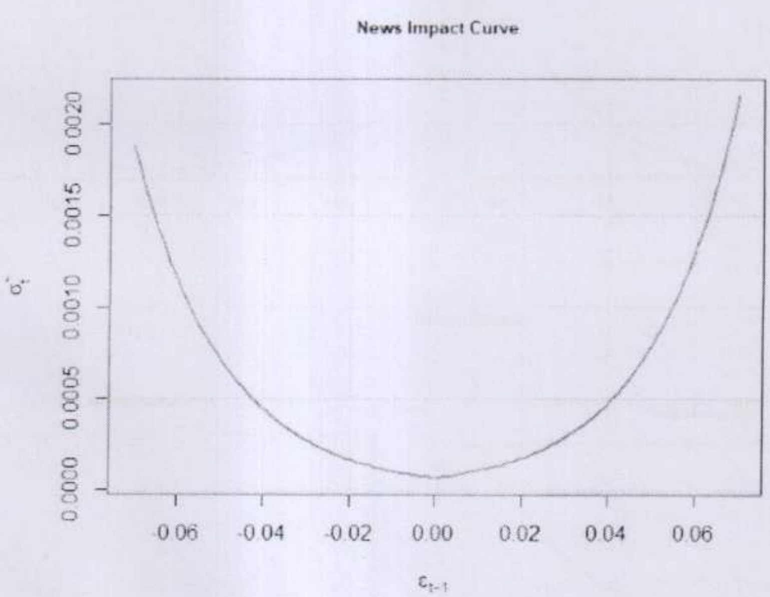
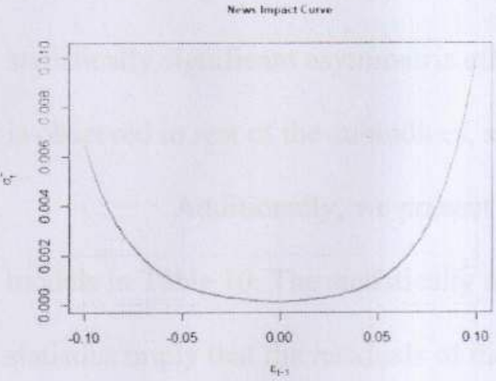
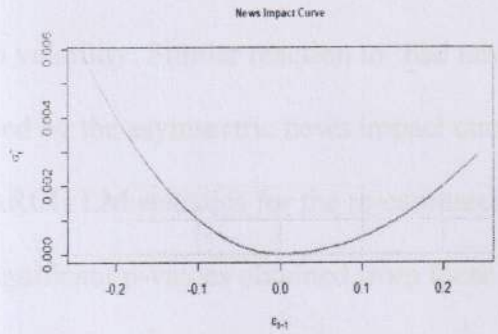


Figure 6 *News Impact on Volatility of Return Series of NEPSE*

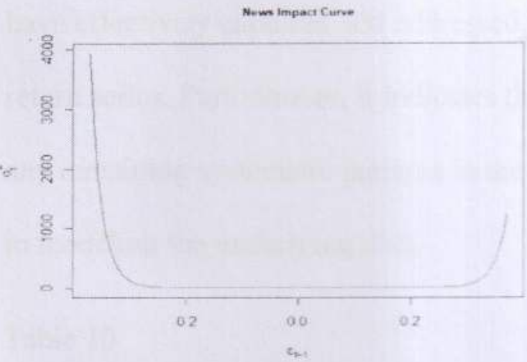
Commercial Bank



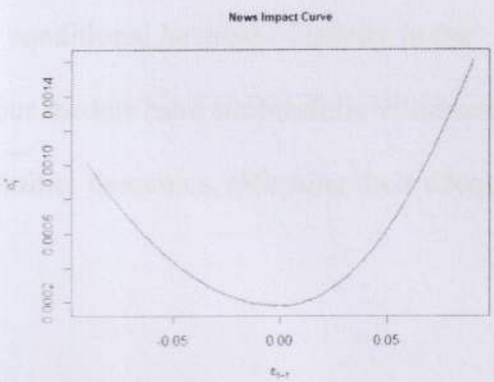
Development Bank



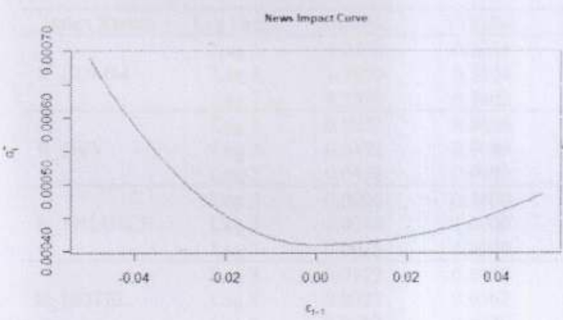
Finance



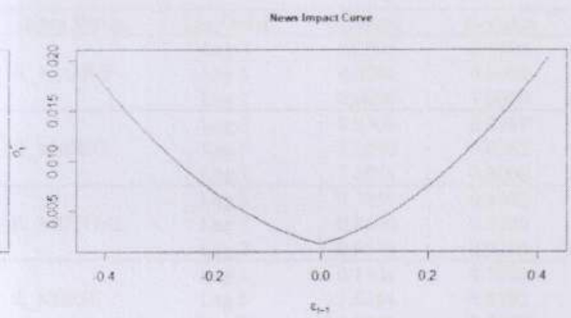
Hotel



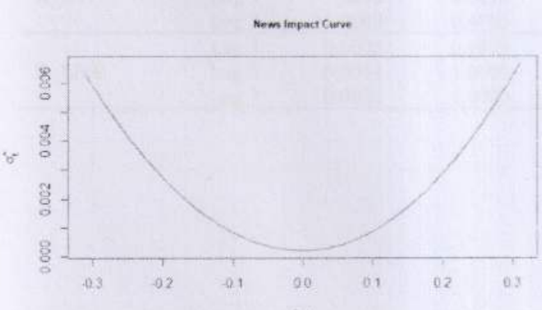
Investment



Life



Manufacturing



Microfinance

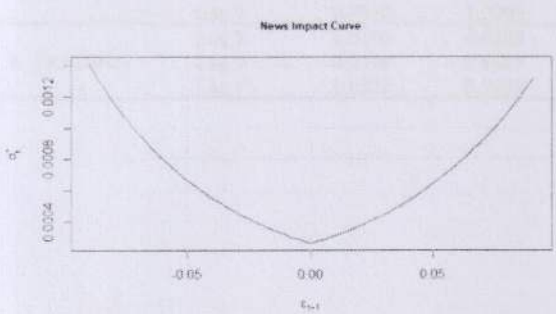


Figure 7 *News Impact on Volatility*

Figure 7 shows the news impact of the rest of the nine indices having statistically significant asymmetric effect in volatility. Similar reaction to 'bad news' is observed in rest of the subindices, signified by the asymmetric news impact curve.

Additionally, we present the ARCH LM statistics for the re-estimated models in Table 10. The statistically non-significant p-values obtained from these statistics imply that the residuals of the $ARMA(p,q) - GARCH(1,1)$ models do not exhibit any significant autocorrelation. This observation signifies that our models have effectively captured and addressed the conditional heteroskedasticity in the return series. Furthermore, it indicates that our models have successfully eliminated any remaining systematic patterns in the volatility dynamics, affirming their adequacy in modeling the underlying data.

Table 10

ARCH LM Statistics of Re-estimated GARCH Specification

Index Return	Lag Order	Statistic	P-Value	Index Return	Lag Order	Statistic	P-Value
R_COMM	Lag 3	1.2470	0.2641	R_MANUF	Lag 3	0.0025	0.9600
	Lag 5	1.7000	0.5414		Lag 5	0.0060	0.9998
	Lag 7	1.7970	0.7602		Lag 7	0.0090	1.0000
R_DEV	Lag 3	0.0052	0.9426	R_MICRO	Lag 3	0.9308	0.3347
	Lag 5	0.0172	0.9989		Lag 5	1.2650	0.6562
	Lag 7	0.0458	0.9999		Lag 7	1.6054	0.8000
R_FINANCE	Lag 3	0.0006	0.9800	R_MUTUAL	Lag 3	0.7259	0.3942
	Lag 5	0.0016	1.0000		Lag 5	0.8696	0.7720
	Lag 7	0.0025	1.0000		Lag 7	0.9539	0.9210
R_HOTEL	Lag 3	0.0172	0.8957	R_NEPSE	Lag 3	0.1403	0.7080
	Lag 5	0.0377	0.9967		Lag 5	1.6284	0.5592
	Lag 7	0.0493	0.9999		Lag 7	2.0582	0.7050
R_HYDRO	Lag 3	2.9790	0.0844	R_NONLIFE	Lag 3	0.3030	0.5820
	Lag 5	5.6810	0.0714		Lag 5	0.3106	0.9374
	Lag 7	7.2800	0.0756		Lag 7	0.7223	0.9541
R_INV	Lag 3	1.4150	0.2342	R_OTHER	Lag 3	0.0003	0.9864
	Lag 5	1.4650	0.6016		Lag 5	0.0007	1.0000
	Lag 7	3.0800	0.4985		Lag 7	0.0010	1.0000
R_LIFE	Lag 3	0.0005	0.9829	R_TRADING	Lag 3	0.0100	0.9202
	Lag 5	0.0014	1.0000		Lag 5	0.0199	0.9987
	Lag 7	0.0021	1.0000		Lag 7	0.0358	0.9999

CHAPTER V
SUMMARY, DISCUSSION, AND IMPLICATIONS

The primary aim of this research was to examine the volatility characteristics within the Nepalese capital market comprehensively. The research sought to address key questions related to the extent of volatility persistence and the presence of a leverage effect across various indices of the broader Nepal Stock Exchange. In pursuit of a more nuanced understanding, this study also considered deterministic structural breaks and studied their impact on the persistence and leverage parameters.

The results and findings from this study pertaining to the nature of volatility were then synthesized within the context of two prominent theoretical frameworks: the Efficient Market Hypothesis and the Adaptive Market Hypothesis. This synthesis aimed to provide valuable insights into the level of market efficiency within the Nepalese capital market, shedding light on the underlying dynamics and implications for investors and stakeholders alike.

This chapter is segmented into five sections comprising summary, discussion, conclusion, research implication and critique.

Summary

This study's objective was to empirically analyze 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. Families of GARCH specifications were used to capture the asymmetric effects. Previous studies have explored volatility aspects within the Nepalese market (Dangal & Gajurel, 2021; GC, 2008; Rana, 2020). This study is built on the methodological gap by incorporating deterministic structural breaks, which signify volatility clusters, in its analysis—a facet previously unexamined in extant studies.

Notable studies about volatility in stock market returns have recognized that the persistence of volatility tends to be overestimated when models neglect to account for deterministic structural breaks, a phenomenon elucidated by Lamoureux and Lastrapes (1990). The findings of this study corroborate this observation, indicating that, in several instances, if not all, the estimates of persistence parameters across 7 out of the 14 indices exhibit elevated persistence values.

This investigation's results reveal a leverage effect within the return series, signifying an asymmetric impact of information shocks on expected volatility. Specifically, "negative shocks" wield a more substantial influence than "positive shocks". The impact was enhanced when deterministic structural shifts were considered, adding five more indices to show the leverage effect, which was previously absent.

In contrast to the assumptions of the efficient market hypothesis, wherein investors are regarded as rational actors aiming to maximize the expected utility from investments, this study highlights the propensity of investors to react differently to various types of information shocks. Notably, reactions to positive information shocks are more subdued than negative ones. The presence of a leverage effect is evident in 10 out of 14 indices, aligning with previous studies that have reported a similar pattern in investors' responses to "negative shocks" versus "positive shocks" (Alberg et al., 2008; Ewing & Malik, 2005).

Furthermore, the concurrent presence of both persistence and leverage effects suggests prolonged influences on expected volatility. These findings collectively indicate that prices and return series in the Nepalese capital market do not adhere to a truly random pattern; instead, they exhibit some degree of predictable patterns arising from historical information shocks and volatility. Incorporating informational content into price and return indices is gradual rather than instantaneous.

The existence of varying degrees of unconditional variance, ARCH effects, and GARCH effects across different periods and indices indicates that identical events or information shocks can yield varying levels of impact on volatility. This observation indicated the lack of informational efficiency within the Nepalese capital market. The observed friction, manifested as varying volatility parameters across different indices at different points in time, reflects heterogeneous expectations among participants in the Nepalese capital market. Consequently, this study posits that the Nepalese capital market does not demonstrate a weak form of market efficiency, aligning with prior studies conducted in the Nepalese capital market context (Jha, 2019), while some studies have suggested that the market may exhibit partial efficiency (Dangol, 2016, 2017).

The results and findings of this study offer valuable insights into the volatility dimensions of the Nepalese stock market. While the empirical nature of the study limits the generalizability of findings across different temporal dimensions, given the unfolding nature of future events, the retrospective identification of events leading to structural breaks underscores the significant impact of political and economic events on investment decisions. Further, considering such a deterministic structural shift ensures a more accurate diagnosis of the volatility attribute of the Nepal stock market.

Discussion

The primary objective of this study was to conduct an in-depth analysis of the volatility within the return series of various indices in the context of the Nepal Stock Exchange (NSE). To achieve this extensive dataset spanning multiple years, focusing on high-frequency daily return data from 14 different Nepal Stock Exchange indices were gathered and analyzed. This granular dataset allowed us to capture event-driven volatility and enhance the precision of the volatility measurements, expected to reduce standard errors by accounting for short-term price movements, as suggested by previous studies (Rossana & Seater, 1995; Zhang, 2010).

The analysis revealed noteworthy findings regarding volatility persistence. As presented in Table 8, all persistence coefficients were close to one except for Commercial Bank, Mutual Funds, and NEPSE Index. A persistence coefficient near 1 indicates that past shocks strongly influence current variance. Understanding the persistence of volatility is crucial, as the impact of volatility on stock prices largely depends on the permanence of variance shocks (Poterba & Summers, 1986). Lamoureux and Lastrapes (1990) emphasized that short-term, transitory shocks have a limited impact on securities prices, whereas more persistent volatility has a pronounced effect. However, it is important to note that GARCH models applied to high-frequency data often result in seemingly strong persistent shocks to variance. Therefore, interpreting higher persistence coefficients at face value can be misleading. With this caution, the study by Lamoureux and Lastrapes (1990) suggested that failure to incorporate deterministic structural shifts can bias upward the GARCH estimates of persistence in variance. When these structural breaks were considered, the average persistence parameter decreased to 0.90320, signifying a decrease of 0.0276 overall.

The analysis demonstrates that in 7 instances, the volatility persistence values have decreased, while in three cases, these values have gained statistical significance, in contrast to the results obtained without accounting for structural shifts. This reduction in persistence measures in most cases aligns with the findings of Lamoureux and Lastrapes, reinforcing the significance of incorporating structural shifts in this study. Including deterministic structural shifts in analyzing the Nepal Stock Exchange (NEPSE) and its constituent indices has provided valuable insights. One noteworthy observation of structural shifts is the enhanced responsiveness of both NEPSE and its subindices to recent information and shocks. This heightened responsiveness is evident in the decrease in persistence parameters for most indices, if not all.

Incorporating structural shifts frequently leads to an improved alignment of the volatility model with the actual data. This enhanced model fit is of great significance as it enables a more accurate representation of financial markets' dynamic and evolving nature. It can enhance risk assessment, improve forecasting accuracy, and facilitate the development of effective trading strategies.

The increased significance of volatility parameters emphasizes the critical importance of robust risk management practices. Investors must exercise heightened vigilance, particularly during periods characterized by structural shifts, as market dynamics can undergo rapid and unpredictable transformations. Based on the above discussions, the first (H1) is partially accepted as the estimate of volatility persistence is found to be biased upwards in the absence of deterministic structural breaks.

The results yielded significant insights into the leverage effect in volatility within the context of the Nepal Stock Exchange and its constituent indices. Initially, the results indicated the leverage effect in five of the 14 indices when deterministic structural shifts were not considered. This observation highlighted the asymmetric nature of market participants' reactions to positive and negative shocks, where negative shocks had a more pronounced impact on volatility.

Meanwhile, introducing deterministic structural breaks into the analysis brought further noteworthy findings. The re-estimation of the leverage parameter in the presence of structural shifts showed the statistically significant asymmetric parameters, denoted by θ_1 in Table 7, which revealed five additional indices with statistically significant leverage effect. Ten indices, including the broader NEPSE index, exhibited a leverage effect when structural shifts were considered. The leverage effect underscores its significance in the Nepalese capital market to characterize the investors' reaction to the good and bad news.

The findings of this research are in contrast with Rana (2020), which failed to confirm the presence of the leverage effect using TGARCH (1,1) and EGARCH (1,1) specifications. This difference in results may be attributed to the inclusion of deterministic structural breaks in the analysis, unveiling the leverage effect that was not previously detected.

The result indicates the nature of market participants in the Nepalese capital market who tend to react asymmetrically to positive and negative shocks, with negative shocks having a more significant impact on volatility. Moreover, including structural breaks in the analysis is crucial in accurately identifying the presence of the leverage effect, highlighting the importance of considering market dynamics when assessing such market anomalies. This evidence provides the partial support for second hypothesis (H2) which stated that the leverage effect in Nepal stock exchange is biased upward in absence of deterministic structural breaks. In four of 14 cases, the measure of leverage parameters has decreased when structural shifts are considered. While six more indices showed the statistically significant leverage effect, which was absent when structural breaks were not considered for.

Hypothesis 3a (H3a) indicated that the measure of volatility persistence with structural breaks indicates the weak form of market inefficiency in the Nepal Stock Exchange. The analysis has yielded significant insights into the persistence of volatility in the Nepal Stock Exchange (NEPSE) when accounting for structural breaks. As outlined in the earlier discussion section, incorporating deterministic structural shifts has reduced the persistence parameters of most NEPSE indices. This reduction suggests that the influence of past shocks on current variance becomes less enduring over time. The weakening of volatility persistence with structural breaks suggests a more adaptive market responsive to recent information and shocks. In the context of the weak form of market efficiency, this result implies that past price and volatility patterns have a diminishing impact on future prices. Market participants in the Nepal Stock Exchange appear to adjust new information, and the influence of past volatility implies a gradual convergence to equilibrium. The decrease in volatility persistence with the introduction of structural breaks supports Hypothesis 3a. It indicates that the Nepal Stock Exchange leans toward the weak form of market efficiency, where historical price and volatility patterns have limited predictive power over future movements.

Hypothesis 3b (H3b) indicated that the measure of leverage with structural breaks indicates the weak form of market inefficiency in the Nepal Stock Exchange. Analyzing the leverage effect in the Nepal Stock Exchange, both with and without structural breaks, has provided valuable insights into market behavior. When structural shifts were not considered, we identified a leverage effect in five of the 14 indices. However, introducing structural breaks revealed statistically significant asymmetric parameters in five additional indices, suggesting that many indices, including the broader NEPSE index, exhibit a leverage effect.

The presence of the leverage effect, particularly when structural shifts are accounted for, carries significant implications for market efficiency. The leverage effect signifies that market participants react differently to "bad news" than "good news." The analysis confirmed the amplified reaction to negative information and a subdued response to positive information, which aligns with the behavioral tendencies outlined in the Prospect Theory.

Therefore, the results and findings of this study support the contention of Hypothesis 3b, as the presence of the leverage effect, especially with structural breaks considered, suggests a market that is not fully efficient in the weak form. Market participants in the NEPSE exhibit behavioral biases that lead to deviations from the purely rational and efficient behavior posited by the EMH. This departure from market efficiency highlights the influence of investor sentiment and behavioral biases on asset prices in the Nepal Stock Exchange.

The postulation of Adaptive Market Hypothesis (Lo, 2004) provided the compelling argument to reconcile the observed difference between behavioral critics and EMH. The AMH considers the influence of human behavior on financial markets and explains how inefficiencies are exerted in the market. These inefficiencies give rise to arbitrage opportunities giving the market a much-required incentive to curb those opportunities to obtain profit. As those arbitrage opportunities are exploited, market inefficiency gradually disappears. But new opportunities are also constantly created as institutions and business conditions change. Like the discourse shown by nature as certain species die out, as others are born.

Conclusion

Considering the study's results and findings, it is evident that the Nepalese capital market exhibits persistence and the leverage effect within the return series across the study's period in the case of most of the indices. These results and findings underscore the importance of past shocks and historical volatility as significant factors influencing the expected volatility. Notably, when deterministic structural breaks were introduced into the model, there was an enhancement in the model's fit and a corresponding reduction in the estimates of persistence and leverage.

This methodological refinement addresses a crucial aspect often overlooked in prior research conducted within the Nepal Stock Exchange context. Furthermore, when examined retrospectively, these structural breaks were associated with significant events, including general and local elections, changes in government, alterations in monetary policies, regulatory adjustments affecting interest rates, foreign reserve policies, and changes in lending practices, particularly concerning margin loans. Additionally, the study unveiled the influence of the global pandemic on the Nepalese capital market.

Based on these findings, it is reasonable to conclude that the Nepalese capital market demonstrates signs of weak-form inefficiency. The higher persistence parameters suggest that the market participants can gauge the expected volatility based on information concerning past conditional volatility and information shocks. Meanwhile, the market exhibits an asymmetric response, reacting differently to "bad news" compared to "good news," particularly when past information shocks are considered in the analysis.

Implication of the Study

This study provides valuable insights for academic researchers and practitioners to understand the nature of volatility of Nepalese capital market. The major theoretical and managerial implications are described in the following section.

Theoretical Implication

This research provides a meaningful contribution to understanding the Nepalese capital market from a volatility perspective. This research provides a unique perspective by incorporating the deterministic structural breaks in estimating the parameter, which should have been more considered in the extant research. It was noted 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 daily financial time-series data usually lacked normality with fat-tailed distribution; however, the volatility analysis is based on the normal distribution in this study. Alberg et al. (2008) showed that overall estimation can be improved by using the asymmetric GARCH with fat-tailed densities for measuring conditional variances. Thus, further studies can be conducted to find a suitable model considering the fat-tailed distribution such as Student-t or skewed Student-t. The research methodology under this study requires finding the deterministic structural shifts in the return series, signifying the volatility clusters. Later, the identified break dates were traced with the events surrounding the break dates, which disclosed the events significantly affecting the volatility. More comprehensive studies can be conducted across specific events to understand event-specific volatility attributes.

Practical Implication

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

Furthermore, these research findings are not limited to investment; they are relevant for regulatory bodies and policymakers. By identifying the events that trigger substantial structural shifts in volatility, this study provides valuable information that can be used to devise and refine regulations and frameworks to ensure financial markets' stability. Policymakers can use these insights to design policies that mitigate potential disruptions and enhance the overall resilience of the market structure.

Moreover, the study's observation of sectorial rotation and shifts in the impact of events across various indices has practical implications for risk management. Investors can use this information to adjust their portfolios in response to sector-specific events, reducing their exposure to risks associated with industries or sectors.

This adaptability can be valuable in managing risk and optimizing investment strategies.

Critique of the Study

It is important to acknowledge the inherent limitations present in the current study. The primary objective of this study was to analyze the volatility aspect of the return series of the Nepalese capital market. For this purpose, all the major indices are considered for the analysis. The aggregation of the stock price of individual assets in the index might result in a loss of information due to offsetting the variance of one stock for another.

The persistence and leverage effect results obtained for indices may not completely reflect the volatility attribute of the individual stocks listed in NEPSE. While evaluating the volatility models, the errors were assumed to be normally distributed; meanwhile, extant literature showed that results could be improved when error distribution addressing the fat-tailed data can be considered. This study limits only the identification of the deterministic structural breaks and tracing it to the events surrounding the event dates. It, however, did not consider the classification and evaluation of such events and their degree of impact on the volatility for a given period. The scope of this research can be furthered to analyze the event-specific volatility. The empirical nature of the study limits the ability to deduce any generalized attribute of volatility beyond the study period.

This study did not involve forecasting, which restricts the ability to test the reliability and validity of the identified volatility models. This study further opens the avenues for studying the contagion effect of any specific events on the volatility and return attribute of indices. The asymmetry in response to volatility across the indices showed that the effects are not uniform and usually manifested in sectorial rotation, or more specifically, contagion property is observed. This study cannot confirm the deterministic sequence or order of such sectorial rotation and shifts, which may be a valuable insight in understanding the investment pattern of Nepalese investors in NEPSE.

REFERENCES

Abdelzaher, M. A. (2021). Study the Efficiency Hypothesis in the Egyptian Stock Market. *International Journal of Economics and Financial Issues*, *11*(1), 18–25. https://doi.org/10.32479/ijefi.10634

Abdennadher, E., & Hellara, S. (2018). Structural Breaks and Stock Market Volatility in Emerging Countries. *International Journal of Business and Risk Management*, *1*(1), 9–16. https://doi.org/10.12691/ijbrm-1-1-2

Adhikari, N., & Phuyal, R. K. (2016). Influence of Political Events on Stock Market Volatility in Nepal. *International Journal of Economic Research*, *13*(7), 2765–2778.

Aggarwal, R., Inclan, C., & Leal, R. (1999). Volatility in Emerging Stock Markets. *The Journal of Financial and Quantitative Analysis*, *34*(1), 33. https://doi.org/10.2307/2676245

Alberg, D., Shalit, H., & Yosef, R. (2008). Estimating Stock Market Volatility using Asymmetric GARCH Models. *Applied Financial Economics*, *18*(15), 1201–1208. https://doi.org/10.1080/09603100701604225

Antony, A. (2019). Behavioral Finance and Portfolio Management: Review of Theory and Literature. *Journal of Public Affairs*, *20*(2), 1–7. https://doi.org/10.1002/pa.1996

Assaf, A. (2016). MENA Stock Market Volatility Persistence: Evidence Before and After the Financial Crisis of 2008. *Research in International Business and Finance*, *36*, 222–240. https://doi.org/10.1016/j.ribaf.2015.09.003

Asteriou, D., & Hall, G. S. (2021). *Applied Econometrics* (4th ed.). macmillan international Higher Education.

Bachelier, L. (1900). *Theorie de la Speculation* (3rd ed., Vol. 17). Annales scientifiques de l'É.N.S.

Bai, J., & Perron, P. (1998). Estimating and Testing Linear Models with Multiple Structural Changes. *The Econometric Society*, *66*(1), 47–78. http://www.jstor.org/stable/2998540

Bai, J., & Perron, P. (2003a). Computation and Analysis of Multiple Structural Change Models. *Journal of Applied Econometrics*, *18*(1), 1–22. https://doi.org/10.1002/jae.659

Bai, J., & Perron, P. (2003b). Critical Values for Multiple Structural Change Tests. *The Econometrics Journal*, *6*(1), 72–78. https://doi.org/10.1111/1368-423x.00102

Ball, R., & Brown, P. (1968). An Empirical Evaluation of Accounting Income Numbers. *Journal of Accounting Research*, *6*(2), 159–178. http://www.journals.uchicago.edu/t-an

Bartov, E., Radhakrishnan, S., & Krinsky, I. (2000). Investor Sophistication and Patterns in Stock Returns after Earnings Announcements. *Accounting Review*, *75*(1), 43–63. https://doi.org/10.2308/accr.2000.75.1.43

Beaulieu, M. C., Cosset, J. C., & Essaddam, N. (2006). Political Uncertainty and Stock Market Returns: Evidence from the 1995 Quebec Referendum. *Canadian Journal of Economics*, *39*(2), 621–642. https://doi.org/10.1111/j.0008-4085.2006.00363.x

Bechtel, M. M. (2009). The Political Sources of Systematic Investment Risk: Lessons from a Consensus Democracy. *Journal of Politics*, *71*(2), 661–677. https://doi.org/10.1017/S0022381609090525

Białkowski, J., Gottschalk, K., & Wisniewski, T. P. (2008). Stock Market Volatility Around National Elections. In *Journal of Banking and Finance* (Vol. 32, Issue 9, pp. 1941–1953). https://doi.org/10.1016/j.jbankfin.2007.12.021

Bollerslev, T. (1986). General Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, *31*(1), 307–327. https://doi.org/10.1109/TNN.2007.902962

Bollerslev, T. (1987). A Conditionally Heteroskedastic Time Series Model for Speculative Press and Rates of Return. *The Review of Economics and Statistics*, *69*(3), 542–547.

Bollerslev, T., Engle, R. F., & Nelson, D. B. (1994). ARCH models. In R.F Engle & D. . McFadden (Eds.), *Handbook of Econometrics: Vol. IV* (pp. 2961–2984). Elsevier Inc. https://doi.org/https://doi.org/10.1016/S1573-4412(05)80018-2

Campello, D. (2007). Do Markets Vote? A Systematic Analysis of Portfolio Investors' Response to National Elections. In *Department of Political Science, Princeton University*. http://danicamp.bol.ucla.edu/Danicamp files/Do Markets Vote.pdf

Chan, S. (2003). Judgment Heuristics and Prospect Theory : Some Practical Implications for Relations across the Taiwan Strait. *Journal of East Asian Studies*, *3*(1), 75–95.

Chau, F., Deesomsak, R., & Wang, J. (2014). Political Uncertainty and Stock Market Volatility in the Middle East and North African (MENA) Countries. *Journal of*

International Financial Markets, Institutions and Money, *28*(1), 1–19. https://doi.org/10.1016/j.intfin.2013.10.008

Chavali, K., Alam, M., & Rosario, S. (2020). Stock Market Response to Elections: An Event Study Method. *Journal of Asian Finance, Economics and Business*, *7*(5), 9–18. https://doi.org/10.13106/JAFEB.2020.VOL7.NO5.009

Chesney, M., Reshetar, G., & Karaman, M. (2011). The Impact of Terrorism on Financial Markets: An Empirical Study. *Journal of Banking and Finance*, *35*(2), 253–267. https://doi.org/10.1016/j.jbankfin.2010.07.026

Cowles, A., & Jones, H. (1937). A Posteriori Probabilities in Stock Market Action. *Econometrica*, *5*(3), 280–294.

Dangal, D. N., & Gajurel, R. P. (2021). Volatility of Daily Nepal Stock Exchange (Nepse) Index Return: A GARCH Family Models. *Tribhuvan University Journal*, *36*(01), 31–44. https://doi.org/10.3126/tuj.v36i01.43514

Dangol, J. (2008). Unanticipated Political Events and Stock Returns: An Event Study. *Economic Review*, *20*(2006), 86–110. https://archive.nrb.org.np/ecorev/pdffiles/vol20_art7.pdf

Dangol, J. (2016). Nepalese Stock Market Efficiency in Respect of Cash and Stock Dividend Announcement. *Indian Journal of Commerce & Management Studies*, *7*(3), 6–71. http://scholarshub.net/ijcms/vol7/issue3/Paper_09.pdf)

Dangol, J., & Bhandari, A. (2019). Quarterly Earnings Announcement Effect on Stock Return and Trading Volume in Nepal. *International Research Journal of Management Science*, *4*(1), 32–47. https://doi.org/10.3126/irjms.v4i0.27884

Diebold, F. X., & Inoue, A. (2001). Long Memory and Regime Switching. *Journal of*

Econometrics, *105*(1), 131–159. https://doi.org/10.1016/S0304-4076(01)00073-2

Ding, Z., Granger, C. W. J., & Engle, F. (1993). A Long Memory Property of Stock Market Returns and a New Model. *Journal of Empirical Finance*, *2*(1), 83–106. https://doi.org/10.1016/0927-5398(95)90049-7

Engle, Robert. F. (1982). Autoregressive Conditional Heteroscedacity with Estimates of Variance of United Kingdom Inflation. In *Econometrica* (Vol. 50, Issue 4, pp. 987–1008).

Ewing, B. T., & Malik, F. (2005). Re-examining the Asymmetric Predictability of Conditional Variances: The Role of Sudden Changes in Variance. *Journal of Banking and Finance*, *29*(10), 2655–2673. https://doi.org/10.1016/j.jbankfin.2004.10.002

Fama, E. F. (1991). Efficient Capital Markets: II. *The Journal of Finance*, *XLVI*(5), 1575–1617.

Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969). Adjustment of Stock Prices to New Information. *International Economic Review*, *10*(1), 1–21.

Fang, M., Yang, S., & Lei, Y. (2019). Residual Contagion in Emerging Markets: 'Herd' and 'Alarm' Effects in Informatization. *Electronic Commerce Research*, *0123456789*. https://doi.org/10.1007/s10660-019-09350-x

Ferreira, S., & Karali, B. (2015). Do Earthquakes Shake Stock Markets? *PLoS ONE*, *10*(7), 1–19. https://doi.org/10.1371/journal.pone.0133319

GC, S. (2008). Volatility Analysis of Nepalese Stock Market. *Journal of Nepalese Business Studies*, *5*(1), 76–84. http://www.nepjol.info/index.php/JNBS/article/viewArticle/2085

Ghalanos, A. (2022). *Introduction to the Rugarch Package* (pp. 1–36).

Glosten, L. R., Jagannath, R., & Runkle, D. E. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *The Journal of Finance*, *48*(5), 1779–1801. https://doi.org/10.1111/j.1540-6261.1993.tb05128.x

Granger, C. W. J., & Hyung, N. (2004). Occasional Structural Breaks and Long Memory with an Application to the S&P 500 Absolute Stock Returns. *Journal of Empirical Finance*, *11*(3), 399–421. https://doi.org/10.1016/j.jempfin.2003.03.001

Grossman, S. J., & Stiglitz, J. E. (1980). On the Impossibility of Informationally Efficient Markets. *The American Economic Review*, *70*(3), 393–408.

Hamilton, J. D., & Susmel, R. (1994). Autoregressive Conditional Heteroskedasticity and Changes in Regime. *Journal of Econometrics*, *64*(1–2), 307–333. https://doi.org/10.1016/0304-4076(94)90067-1

Hashim, N., & Mosallamy, D. El. (2020). Presidential Elections and Stock Market: A Comparative Study. *Journal of Finance and Economics*, *8*(3), 116–126. https://doi.org/10.12691/jfe-8-3-4

He, P., Sun, Y., Zhang, Y., & Li, T. (2020). COVID–19's Impact on Stock Prices Across Different Sectors—An Event Study Based on the Chinese Stock Market. *Emerging Markets Finance and Trade*, *56*(10), 2198–2212. https://doi.org/10.1080/1540496X.2020.1785865

Jha, S. (2019). *Testing the Adaptive Market Hypothesis in Nepal Stock Exchange*. Kathmandu University.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, *47*(2), 263–292. https://doi.org/10.2307/1914185

Kendall, M. G., & Hill, A. B. (1953). The Analysis of Economic Time-Series-Part I: Prices. *Journal of the Royal Statistical Society. Series A (General)*, *116*(1), 11–34.

Kirana, N., & Sembel, R. (2019). The Effect of Political Event on the Indonesian Stock Market: An Event Study of Presidential Election on LQ45 Index Stocks. *International Journal of Business, Economics and Law*, *19*(1), 40–49.

Kohonen, A. (2013). On Detection of Volatility Spillovers in Overlapping Stock Markets. *Journal of Empirical Finance*, *22*, 140–158. https://doi.org/10.1016/j.jempfin.2013.04.005

Lamoureux, C. G., & Lastrapes, W. D. (1990). Persistene in Variance, Structural Change, and the GARCH Model. *Journal of Business*, *8*(2), 225–234.

Lo, A. W. (2004). The Adaptive Market Hypothesis. *The Journal of Portfolio Management*.

Mandelbrot, B. (1966). Forecasts of Future Prices, Unbiased Markets, and Martingale Models. *The Journal of Business*, *39*(1), 242–255.

Markowitz, H. (1952). Portfolio Selecion. *Journal of Finance*, *7*(1), 77–91.

Nazir, M. S., Younus, H., Kaleem, A., & Anwar, Z. (2014). Impact of Political Events on Stock Market Returns: Empirical Evidence from Pakistan. *Journal of Economic and Administrative Sciences*, *30*(1), 60–78. https://doi.org/10.1108/jeas-03-2013-0011

Nelson, D. B. (1991). Conditional Heteroskedasticity in Asset Returns : A New

Approach. *Econometrica*, *59*(2), 347–370.

Odean, T. (1998). Are Investors Reluctant to Realize their Losses? *The Journal of Finance*, *LIII*(5), 1775–1798. https://doi.org/10.1017/CBO9780511803475.022

Önder, Z., & Şimga-Muğan, C. (2006). How Do Political and Economic News Affect Emerging Markets? *Emerging Markets Finance and Trade*, *42*(4), 50–77. https://doi.org/10.2753/REE1540-496X420403

Osborne, M. (1959). Brownian Motion in the Stock Market. *Operation Research*, *7*(2), 145–173. https://doi.org/10.1515/les.1979.24.3.108

Pasewark, W. R., & Riley, M. E. (2010). It's a matter of principle: The role of personal values in investment decisions. *Journal of Business Ethics*, *93*(2), 237–253. https://doi.org/10.1007/s10551-009-0218-6

Raddant, M., & Kenett, D. Y. (2021). Interconnectedness in the Global Financial Market. *Journal of International Money and Finance*, *110*, 102280. https://doi.org/10.1016/j.jimonfin.2020.102280

Rana, S. B. (2020). Dynamics of Time Varying Volatility in Stock Returns: Evidence from Nepal Stock Exchange. *Journal of Business and Social Sciences Research*, *5*(1), 15–34. https://doi.org/10.3126/jbssr.v5i1.30196

Ricciardi, V., & Simon, K. H. (2000). What Is Behavioral Finance? *Business, Education, and Technology Journal*, *2*(2), 1–9. https://doi.org/10.1002/9780470404324.hof002009

Richards, I. M. (1975). The Reaction of the Stock Market to Non-Financial Information. In *ProQuest LLC* (Vol. 30, Issue 3). University of Manchester.

Roberts, H. V. (1959). Stock-Market " Patterns " and Financial Analysis :

Methodological Suggestions. *The Journal of Finance*, *14*(NO.1), 1–10.

Samarakoon, L. P. (2011). Stock Market Interdependence, Contagion, and the U.S. Financial Crisis: The Case of Emerging and Frontier Markets. *Journal of International Financial Markets, Institutions and Money*, *21*(5), 724–742. https://doi.org/10.1016/j.intfin.2011.05.001

Samuelson, P. A. (1965). Proof That Properly Anticipated Prices Fluctuate Randomly. *Industrial Management Review*, *6*(2), 41–49.

Scholes, M. S. (1972). The Market for Securities: Substitution Versus Price Pressure and the Effects of Information on Share Prices. *The Journal of Business*, *45*(2), 179. https://doi.org/10.1086/295444

Securities Exchange Board of Nepal. (2022). *Annual Report 2021/22.*

Sharpe, W. F. (1964). Capital Asset Prices: a Theory of Market Equilibrium Under Conditions of Risk. *The Journal of Finance*, *19*(3), 425–442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Syed, A. M., & Bajwa, I. A. (2018). Earnings Announcements, Stock Price Reaction and Market Efficiency – The Case of Saudi Arabia. *International Journal of Islamic and Middle Eastern Finance and Management*, *11*(3), 416–431. https://doi.org/10.1108/IMEFM-02-2017-0044

Thaler, R. H. (1999). Mental Accounting Matters. *Journal of Behavioral Decision Making*, *12*(3), 183–206. https://doi.org/10.1017/CBO9780511803475.015

Tripathy, T., & Gil-Alana, L. A. (2015). Modelling Time-varying Volatility in the Indian Stock Returns: Some Empirical Evidence. *Review of Development Finance*, *5*(2), 91–97. https://doi.org/10.1016/j.rdf.2015.04.002

Wong, W. Y., & Hooy, C. W. (2021). Market Response Towards Different Types of Politically Connected Firms During Political Events: Evidence from Malaysia. *International Journal of Managerial Finance*, *17*(1), 49–71. https://doi.org/10.1108/IJMF-09-2019-0331

Working, H. (1934). A Random Difference Series for Use in the Analysis of Time Series. *Journal of American Statistical Association*, *29*, 11–24.

Zhang, F. (2010). *High-Frequency Trading, Stock Volatility, and Price Discovery* (Issue 1). Yale University.

Appendix A

GARCH Model Specification Results

Table 11

Standard GARCH Specification with ARMA (p,q)

	Return on Indices													
	COMM	DEV	FINANCE	HOTEL	HYDRO	INV	LIFE	MANU	MICRO	MUTUAL	NEPSE	NONLIFE	OTHER	TRADING
μ	-0.00020	0.00065	-0.00021	0.00011	-0.00002	-0.00034	0.00026	0.00010	0.00071	0.00050	0.00040	-0.00001	-0.00002	0.00038***
δ_1		0.99681***	1.02982			-0.93711***	1.01458***	0.92315	0.77570***	-0.50647***		0.83712***		-0.93709***
δ_2		-0.20264**	-0.11294			-0.56945***	-0.05679	-0.06899						0.90597***
δ_3		0.09000	0.07667					-0.00033						-0.04466***
γ_1	0.27517***	-0.77819	-0.88644*		0.19423***	1.08677***	-0.83350***	-0.81067	-0.61358**	0.64415***	0.28828***	-0.70922***	-0.00411	
γ_2					-0.00535	0.54469***	-0.07182*		-0.18156**		0.00897	-0.20232***		
γ_3									0.07721**			0.14233***		
ω	0.0000	0.0000	0.0000	0.0000***	0.0000***	0.0000	0.0000*	0.0000	0.0000***	0.0000	0.0000***	0.0000	0.0000	0.0000***
α_1	0.3977***	0.0412***	0.2079	0.1098***	0.2894***	0.0609	0.1940***	0.0627	0.1806***	0.0000	0.3027***	0.1192*	0.0735	0.0914***
β_1	0.5458***	0.9529***	0.7911	0.8892***	0.6110***	0.8686***	0.8050***	0.9300	0.7912	0.9990***	0.6835***	0.8310***	0.9241*	0.9261***
Persistence	0.9435	0.9941	0.9990	0.9990	0.9004	0.9295	0.9990	0.9927	0.9718	0.9990	0.9862	0.9501	0.9976	1.0175
LogLik	13322.03	13638.81	15046.62	13966.38	9724.86	1201.94	13867.11	14169	3366.70	2006.68	14310.71	2799.26	12895.95	13950.61
AIC	-5.8886	-6.0273	-6.6498	-6.1739	-5.4069	-4.9541	-6.1283	-6.2619	-5.4613	-6.3213	-6.3253	-5.2616	-5.7002	-6.1670
BIC	-5.8815	-6.0160	-6.6385	-6.1683	-5.3966	-4.8848	-6.1169	-6.2505	-5.4280	-6.2791	-6.3168	-5.2241	-5.6931	-6.1571
H-Q	-5.8861	-6.0233	-6.6458	-6.1719	-5.4032	-4.9269	-6.1243	-6.2579	-5.4488	-6.3049	-6.3223	-5.2474	-5.6977	-6.1635

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

Note: The above results are based on the standard GARCH model specification. The mean equation is represented as $r_t = \mu + \Sigma_{i=1}^{P}\delta_i r_{t-i} + \Sigma_{i=1}^{Q}\gamma_i e_{t-i} + e_t$ where errors are distributed normally with zero mean and σ_t^2 conditional to given set of information. δ_i represents the lag of return series of i^{th} order and γ_i represents the lagged error terms of p^{th} order. The variance equation is represented as $\sigma_t^2 = \omega + \beta_1\sigma_{t-1}^2 + \alpha_1 e_{t-1}^2$. β_1 represents the GARCH Term capturing the effect of lagged volatility while α_1 captures the effect of lagged error term representing past information shocks. The parameter constraints imposed in model specification is $\beta_1 \geq 0; \alpha_1 \geq 0; \beta_1 + \alpha_1 \leq 1$. The sum of alpha and beta parameters $(\alpha_1 + \beta_1)$ measures the volatility persistence. While Log-Likelihood, AIC, BIC and H-Q parameters represented the model fit statistics.

Table 12

Standard eGARCH Specification with ARMA (p,q)

	Return on Indices													
	COMM	DEV	FINANCE	HOTEL	HYDRO	INV	LIFE	MANUF	MICRO	MUTUAL	NEPSE	NONLIFE	OTHER	TRADING
μ	-0.00017	0.00041*	-0.00300***	0.00000	-0.00019	-0.00054	0.00096***	0.00093	0.00051	0.00035	0.00014**	0.00013*	0.00000	0.00025
δ_1		1.27555***	1.08493***			-0.95507***	0.84493***	-0.05511	0.74325***	-0.64543***		0.76991***		0.87574
δ_2		-0.33677***	-0.16702***			-0.55567***	0.05489***	0.08131						
δ_3		0.06221***	0.07145***					0.10309						
γ_1	0.27935***	-0.99047***	-0.86925***		0.20092***	1.10601***	-0.66746***	0.16874***	-0.59535***	0.74312***	0.28706***	-0.66072***	-0.05065	-0.81886
γ_2					-0.00201	0.55468***	-0.15030***		-0.16688**		0.00782	-0.17202***		-0.03123
γ_3									0.07906*			0.14021***		
ω	-1.6540***	-0.7924***	-0.4633**	-0.5609***	-1.5078***	-0.7785**	-0.3077***	-1.8080*	-0.5481***	-1.7863**	-0.9882***	-0.6287	-0.9705	-0.3829
α_1	0.0269	-0.0773	-0.1276	0.1912	0.0329	-0.0563	0.0651***	0.0462	-0.0066	0.1144	0.0017	0.0296	0.0813	0.0128
β_1	0.8037***	0.9027***	0.9427***	0.9255***	0.8121***	0.9003***	0.9629***	0.7841***	0.9313***	0.8049***	0.8877***	0.9206***	0.8681	0.9499
θ_1	0.6271***	0.3172***	0.4870**	0.3730***	0.4845***	0.1292	0.1981***	0.3251***	0.3399***	0.2135*	0.5244***	0.2546***	0.7449	0.1952
Persistence	0.8037	0.9027	0.9427	0.9255	0.8121	0.9003	0.9629	0.7841	0.9313	0.8049	0.8877	0.9206	0.8681	0.9499
LogLik	13376	13387	15065	13692	9734	1204	13897	13652	3374	2026	14344	2799	12398	14343
AIC	-5.9118	-5.9156	-6.6577	-6.0520	-5.4111	-4.9597	-6.1412	-6.0328	-5.4721	-6.3795	-6.3397	-5.2597	-5.4797	-6.3387
BIC	-5.9033	-5.9028	-6.6450	-6.0449	-5.3991	-4.8817	-6.1284	-6.0200	-5.4346	-6.3303	-6.3297	-5.2175	-5.4712	-6.3273
H-Q	-5.9088	-5.9111	-6.6532	-6.0495	-5.4069	-4.9290	-6.1367	-6.0283	-5.4580	-6.3604	-6.3362	-5.2437	-5.4767	-6.3347

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

Note: The above results are based on the Exponential GARCH model specification. The mean equation is represented as $r_t = \mu + \Sigma_{i=1}^{P}\delta_i r_{t-i} + \Sigma_{i=1}^{Q}\gamma_i e_{t-i} + e_t$ where errors are distributed normally with zero mean and σ_t^2 conditional to given set of information. δ_i represents the lag of return series of i^{th} order and γ_i represents the lagged error terms of p^{th} order. The variance equation is represented as $\ln(\sigma_t^2) = \omega + \beta_1 \ln(\sigma_{t-1}^2) + \alpha_1 \left|\left(\frac{e_{t-1}}{\sqrt{\sigma_{t-1}^2}}\right)\right| + \theta_1 \frac{e_{t-1}}{\sqrt{\sigma_{t-1}^2}}$. β_1 *and* α_1 captures the GARCH and ARCH effect while θ_1 measures the leverage effect. The beta parameter β_1 captures the persistence. While Log-Likelihood, AIC, BIC and H-Q parameters represented the model fit statistics.

Table 13

Standard GJR Specification with ARMA(p,q)

	Return on Indices													
	COMM	DEV	FINANCE	HOTEL	HYDRO	INV	LIFE	MANUF	MICRO	MUTUAL	NEPSE	NONLIFE	OTHER	TRADING
μ	-0.0002	0.0053	-0.0003	0.0001	0.0001	-0.0007	0.0003	0.0001	0.0005	0.0007***	0.0004	0.0000	0.0000	0.0003
δ_1		0.8929	0.9969			-0.9533***	1.0121***	0.8326***	0.7811***	-0.5426***		0.8384***		0.9239***
δ_2		-0.1462	-0.1202			-0.5807***	-0.0549***	-0.0681***						
δ_3		0.1177	0.0702					0.0089						
γ_1	0.2754***	-0.6930	-0.8551		0.1957***	1.0931***	-0.8316*	-0.7204***	-0.6198***	0.6668***	0.2878***	-0.7109***	-0.0020	-0.9412***
γ_2					-0.0054	0.5694***	-0.0729*		-0.1791***		0.0091	-0.2021***		0.0014***
γ_3									0.0757*			0.1426***		
ω	0.0000	0.0000	0.0000	0.0000	0.0000***	0.0000	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000	0.0000	0.0000***
α_1	0.4098*	0.0500	0.2120	0.1360	0.3110***	0.0304	0.1970	0.0671***	0.1583***	0.0006***	0.2899***	0.1164*	0.0776	0.0500***
β_1	0.5434***	0.9000	0.8047	0.8910***	0.6130***	0.8591	0.8049	0.9301***	0.7939***	0.9994***	0.6836***	0.8314***	0.9219	0.9243***
θ_1	-0.0192	0.0508	-0.0354	-0.0560	-0.0525	0.0814	-0.0058	-0.0039	0.0517	-0.0054***	0.0256	0.0059	-0.0036	0.0494
Persistence	0.9435	0.9753	0.9990	0.9990	0.8978	0.9303	0.9990	0.9953	0.9781	0.9973	0.9862	0.9507	0.9976	0.9990
LogLik	13322.16	13141.54	15047.36	13975.38	9726.14	1204.83	13867.17	14171.89	3367.76	2008.12	14311.18	2799.28	13025.83	13971.83
AIC	-5.8882	-5.8070	-6.6497	-6.1775	-5.4070	-4.9620	-6.1279	-6.2626	-5.4614	-6.3227	-6.3251	-5.2597	-5.7572	-6.1746
BIC	-5.8797	-5.7942	-6.6370	-6.1704	-5.3950	-4.8839	-6.1151	-6.2498	-5.4240	-6.2735	-6.3152	-5.2176	-5.7487	-6.1632
H-Q	-5.8852	-5.8025	-6.6452	-6.1750	-5.4027	-4.9313	-6.1234	-6.2581	-5.4473	-6.3036	-6.3216	-5.2438	-5.7542	-6.1706

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

Note: The above results are based on the GJR GARCH model specification. The mean equation is represented as $r_t = \mu + \Sigma_{i=1}^{P}\delta_i r_{t-i} + \Sigma_{i=1}^{Q}\gamma_i e_{t-i} + e_t$ where errors are distributed normally with zero mean and σ_t^2 conditional to given set of information. δ_i represents the lag of return series of i^{th} order and γ_i represents the lagged error terms of p^{th} order. The variance equation is represented as $\sigma_t^2 = \omega + \beta_1\sigma_{t-1}^2 + \theta_1 e_{t-1}^2 d_{t-1} + \alpha_1 e_{t-1}^2$ β_1 and α_1 captures the GARCH and ARCH effect while θ_1 measures the leverage effect. The persistence is calculated as the $\alpha_1 + \beta_1 + 0.50 \times \theta_1$. While Log-Likelihood, AIC, BIC and H-Q parameters represented the model fit statistics.

Table 14

Standard APARCH Specification with ARMA(p,q)

	Return on Indices													
	COMM	DEV	FINANCE	HOTEL	HYDRO	INV	LIFE	MANUF	MICRO	MUTUAL	NEPSE	NONLIFE	OTHER	TRADING
μ	-0.0001	-0.0002	-0.0013***	-0.0726***	0.0000	-0.0007	-0.0003	0.0004	0.0005	0.0003	0.0002	0.0002	0.0000	0.0003
δ_1		1.2542***	1.3323***			-0.9443***	1.3821***	-0.2097	0.7138***	-0.6598***		0.7395***		0.9294***
δ_2		-0.2726***	-0.3886***			-0.5710	-0.3841***	0.0408						
δ_3		0.0205***	0.0531***					0.0697*						
γ_1	0.2801***	-0.9911***	-0.9931***		0.2042***	1.0830***	-1.2308***	0.3296	-0.5729***	0.7538***	0.2799***	-0.6392***	0.0114	-0.9410***
γ_2					-0.0001	0.5568	0.2389***		-0.1576		0.0070	-0.1620***		-0.0011
γ_3									0.0775**			0.1411***		
ω	0.0065	0.0002	0.0376***	0.0000	0.0018	0.0000	0.0002	0.0000*	0.0015	0.0013	0.0004	0.0015	0.0000	0.0000
α_1	0.3437***	0.1944*	0.4266***	1.0000***	0.2737***	0.0359	0.2052***	0.2033***	0.1815***	0.1091***	0.2855***	0.1406***	0.0780	0.0674**
β_1	0.5626***	0.7952***	-0.3825***	0.0000	0.6412***	0.8666	0.8290***	-0.0448	0.8048***	-0.5679***	0.7073***	0.8172***	0.9280***	0.9208***
θ_1	-0.0911	0.2560*	0.5479***	-0.2200	-0.0845	0.2719	-0.0149	0.5073***	-0.0046	0.7315***	0.0001	-0.1575	-0.0124	0.1507
ϕ	0.7889***	1.3656***	0.2766***	0.0100***	1.0999***	3.3784	1.1220***	2.1332***	0.9084**	1.0857***	1.1746***	0.9795*	1.6801	2.2764***
Persistence	0.8359	0.9603	0.0441	0.9935	0.8613	0.9594	0.9944	0.6659	0.9491	0.2727	0.9388	0.9292	0.9984	0.9986
LogLik	13370	13442	14140	4435	9738	1205	13933	13075	3375	2022	14331	2802	12948	13975
AIC	-5.9089	-5.9392	-6.2521	-1.9585	-5.4131	-4.9589	-6.1566	-5.7811	-5.4708	-6.3744	-6.3340	-5.2636	-5.7225	-6.1755
BIC	-5.8990	-5.9251	-6.2379	-1.9500	-5.3993	-4.8723	-6.1424	-5.7669	-5.4292	-6.3181	-6.3221	-5.2168	-5.7126	-6.1627
H-Q	-5.9090	-5.9342	-6.2471	-1.9555	-5.4081	-4.9249	-6.1516	-5.7761	-5.4551	-6.3526	-6.3294	-5.2459	-5.7190	-6.1710

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

Note: The above results are based on the Asymmetric Power ARCH model specification. The mean equation is represented as $r_t = \mu + \Sigma_{i=1}^{P}\delta_i r_{t-i} + \Sigma_{i=1}^{Q}\gamma_i e_{t-i} + e_t$ where errors are distributed normally with zero mean and σ_t^2 conditional to given set of information. δ_i represents the lag of return series of i^{th} order and γ_i represents the lagged error terms of p^{th} order. The variance equation is represented as $\sigma_t^{\phi} = \omega + \beta_1\sigma_{t-1}^{\phi} + \alpha_1(|e_{t-1}| - \theta e_{t-1})^{\phi}$. $\beta_1 and\ \alpha_1$ captures the GARCH and ARCH effect while θ_1 measures the leverage effect. The persistence is calculated as the $\beta_1 + \alpha_1 k_1$ 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, AIC, BIC, and H-Q parameters represented the model fit statistics.