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# Asymmetric Effect of New York Stock Exchange (NYSE) & London Stock Exchange (LSE): Empirical Evidence

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## Abstracts
The study examines the various asymmetric effects of the New York Stock Exchange (NYSE) and the London Stock Exchange (LSE) over a period from April 1, 2014 to March 31, 2024 by considering daily time series data. The study applies Generalised Autoregressive Conditional Heteroscedastic (GARCH) family models. Here, comparison is made between the New York Stock Exchange (NYSE) and the London Stock Exchange (LSE). The several iterations of the GARCH model effectively captured the fluctuating volatility of returns across time. However, the TARCH and EGARCH models do not show considerable asymmetry in the market returns.

Keywords: NSYE, LSE, GARCH, TGARCH, & EGARCH.

## Introduction
The occurrence of volatility in stock markets has been extensively explored in the domain of applied finance literature. This study investigates various techniques for forecasting volatility of the New York Stock Exchange (NYSE) and the London Stock Exchange (LSE). The First part of the study is based on the New York Stock Exchange (NYSE). The NYSE was founded on May 17, 1792 as a result of the Buttonwood Agreement. It is situated on Wall Street in New York City. The system operates utilising a hybrid concept that combines both electronic and physical trading. The market consists of 2400 listings and has a market value of US$25.564 trillion as of February 2024. It is included in several indices like as the D & J Industrial Average, S&P 500, and NYSE composite. Second part of this study is based on the London Stock Exchange (LSE). The LSE is largely acknowledged as the prominent stock market in Europe. The London School of Economics and Political Science were established on December 30, 1801, making it 222 years old. The LSE is situated in London, England, in the United Kingdom. The FTSE 100 index, also known as "footsie," consists of the 100 largest UK companies listed on the Main Market, selected based on their market capitalisation. The FTSE 100 Index is the primary benchmark for the UK market. The London Stock Exchange (LSE) is a corporation that has been included in many indexes, such as the FTSE 100 Index, 250 Index, 350 Index, Small Cap Index, and FTSE All-Share Index. It has maintained its listing as an issuer since 1918. The current market value of the company

is USD$3.18 trillion as of August 2023. The study employed time series data. The data set consists of the daily closing prices during a period from April 1, 2014, to March 31, 2024. The research has been carried out using symmetric and asymmetric models of GARCH. The study examines the volatility forecasting and makes comparison between NYSE and LSE. The several iterations of the GARCH model accurately represented the changing volatility of returns over time.

The paper has been divided into six different sections. The literature review is described in Section II, the data and research period are examined in Section III, the technique is explained in Section IV, the results are evaluated in Section V, and the conclusion is presented in Section VI.

**Literature Reviews**

A large number of studies have examined the various effects of volatility forecasting. Biswal et al. (2006) investigated the price and volatility spill over between the US and Indian stock markets based on daily data over a period from September 1998 to August 2003. The study uses the ARCH and GARCH models for granger causality and the regression analysis of returns. The study indicates that, although there are notable price spillover effects between the US and Indian stock markets, they do not sufficiently support the volatility spillover effect. Kumar et al. (2007) examine the performances of the MGARCH model to capture the short-run interlink ages between the US and the Indian stock market. The study uses the daily opening and closing returns for daytime and overnight for a period from July 1st, 1999 to June 30th, 2001. The study applies the GARCH model and MGARCH model. The study results quantify the relative importance of NASD visa-a-visa NIFD in predicting nifty overnight return volatility. Mukherjee et al., (2008) examine stock market integration and volatility spillover between Indian and twelve other Asian markets during both trading and non-trading hours. The study examines the time series opening as well as colsing values from November 1997 to April 2008 with the simple GARCH model. The aim of the study is to evaluate the transmission of market information both during market hours and in the absence of trade, such as midnight periods. The study is notably inadequate and indicates that volatility from one market is swiftly transferred to another; yet, some information persists and can be effectively communicated when the market reopens the following day. The study ultimately concluded that the nocturnal market transmission of information is not prevalent between India and all samples. Santos et al., conducted a study in 2014 where they compared various models for predicting volatility in the Brazilian stock market, with a specific emphasis on IBOVESPA. The researchers examine the MIDAS (Mixed Data Sampling) and HAR (Heterogeneous Autoregressive) models, which can incorporate data at various frequencies (daily, weekly, monthly) to capture both long-term and short-term market dynamics. The study also examines the efficacy of integrating various models to enhance the precision of predictions. Their empirical research indicates that the combination of MIDAS and HAR models can produce more reliable predictions of volatility compared to utilising either model individually. This study emphasises the significance of utilising various data frequencies and models to comprehend the intricate characteristics of financial market volatility, providing useful insights for risk management and trading techniques. Banumathy et al., (2015) examines the volatility of nifty index return by using symmetric & asymmetric GRACH models. The study considers the daily closing time series data of nifty indices of ten years. The GARCH models, including GARCH, EGARCH, and TGARCH, are used in the study for the ARCH effect, volatility clustering, and unit root testing. The analysis indicates that coefficient exhibits the anticipated sign in both the EGARCH and TARCH models. The study results indicate that higher risk does not enhance returns, as the coefficient for the selected variables is small. Birau et al., (2015) examines the modeling of the S&P Bombay stock exchange BANKES Index. Volatility patterns using GARCH models. The study considers the closing data for the period of 1st January 2002 to 30th June 2014. The study indicates that the mean and risk value in the BANKEX Index have been integrated, and the results from ACF and PACF demonstrate a diminished degree of both negative and positive patterns, as well as the presence of an autoregressive influence in the series. Chaudhari et al., (2015) examined the efficacy of the ANN framework in forecasting volatility in the Indian stock market. The study employs several input and output configurations utilising two distinct neural architectures and nine learning algorithms, incorporating one hidden layer with the number of hidden neurones changed over three levels (20, 30, and 40). Consequently, the aggregate number of trials is fifty-four. The experimental studies have been conducted with sufficient force throughout three time intervals. Ultimately, the predictive accuracy of the model trained in the present has diminished when tasked with forecasting historical market volatility. Kambouroudis et al., (2016) conducted a comparison of three well-known methods for predicting the volatility of stock returns: GARCH models, implied volatility derived from options pricing, and realised volatility, which is calculated using high-frequency data. The study evaluates the precision of these models over different timeframes and in diverse market circumstances. Their research demonstrates that GARCH models successfully reflect the changing patterns of volatility over time. However, implied volatility offers a more anticipatory and market-driven estimation of future volatility. The utilisation of intraday data in realised volatility enables it to provide robust short-term predictions. Nevertheless, the findings suggest that the integration of different models can improve the accuracy of predictions. The study highlights the merits and drawbacks of each model, indicating that no individual approach is generally superior. However, a mix of methods may result in more reliable predictions of volatility. Another study by Lee et al., (2017) perform a comparative examination of volatility forecasting models in four prominent Asian stock markets, including Malaysia, Indonesia, Hong Kong, and Japan. The study assesses the efficacy of different models, such as GARCH and EGARCH, in forecasting market volatility. Their research suggests that there is no model that consistently performs better than others in all markets. This emphasises the significance of choosing models that are specific to each market, taking into account the local market conditions. EGARCH, due to its capacity to capture asymmetric volatility, demonstrates robust performance in some markets, although classic GARCH models exhibit good performance in other markets. The study highlights the importance of customising methods for predicting volatility, taking into account the variations in economic conditions and market frameworks. Roy (2017) examines the volatility forecasting of sustainable responsible Indices that evaluates various forecasting models to assess their effectiveness in predicting volatility, a critical component for portfolio management and risk assessment. In the study adds value by identifying forecasting methods that best capture the unique volatility patterns of SRI indices. The study findings are particularly relevant for investors seeking to balance ethical considerations with risk management, offering practical insights into the predictability and stability of SRI-focused financial instruments. Kristjanpoller et al., (2018) suggest a hybrid approach for forecasting volatility that combines many methodologies, such as GARCH, artificial neural networks (ANNs), technical analysis, and principle components analysis (PCA). The objective of the project is to improve the accuracy of predictions by integrating conventional econometric models with machine learning and statistical techniques. GARCH models are effective in capturing the changing levels of volatility over time, while artificial neural networks (ANN) excel at detecting intricate nonlinear patterns in data. Principal Component Analysis (PCA) aids in decreasing dimensionality, hence enhancing the computing efficiency of models. Additionally, technical analysis incorporates a market sentiment perspective. The hybrid approach surpasses individual models, emphasising the advantages of incorporating multiple approaches to reflect the complex characteristics of financial market volatility. In 2019, Wang offers fresh perspectives on the correlation between the VIX (Volatility Index) and the prediction of volatility in financial markets. This study examines the potential of the VIX, also known as the "fear gauge," to serve as a predictive indicator of market expectations and enhance the accuracy of volatility predictions. Contrary to conventional models such as GARCH that depend on past data, the VIX integrates market sentiment derived from options prices, providing a more prompt indication of investor expectations. Wang's work illustrates that including the VIX into other forecasting models improves the precision of projecting future volatility. The paper also emphasises the drawbacks of exclusively depending on the VIX, proposing that incorporating it with other econometric and machine learning models produces more reliable predictions. Bhowmik et al., (2020) examines returns and volatility of the stock market using systematic review methods on various financial markets around the world over a period of 2008 to 2019. The study applies various statistical tools and techniques like the GARCH family model and also uses VECM & Granger Causality tests. The study determined that the symmetric information GARCH model elucidates the volatility and return of the data in the context of asymmetric information. The study results, characterised by excellent accuracy, will facilitate the identification of authentic research gaps rather than merely replicating existing studies. Basistha et al., (2020) investigate the effect of covid-19 on the performance of BSE and NSE considering the pre-COVID -19 and COVID-19 based on daily closing data over a period from 3rd September 2019 to 10th July 2020. In the study applies descriptive statistics, the GJR GARCH mode for the indices. The study found that the Indian stock market discloses volatility during the COVID. Also, the study observed that the mean return of both indices is positive pre-COVID and negative during the pandemic. Chaudhary et al., (2020) investigate the impact of COVID-19 on the returns and volatility of stock market indexes in the ten largest economies by GDP. The research analyses daily data from January 2019 to June 2020 utilising multiple statistical methodologies, including descriptive statistics, unit root tests, ARCH, and GARCH model. The study aims to analyse the negative and positive mean returns for all indices in the first and second quarters during the pandemic. The study results that the efficiency in the conditional variance is both positive and significant in its influence across all marketplaces. The analysis indicates that predicting the future price of the security requires consideration of its historical value. Jasuja et al., (2020) examine the effect of COVID-19 on different sectors of Indian economy and analyse the risk and returns during the pandemic period along with measuring volatility. The study considers the daily closing value of indices for the period of 2nd December to 28th April, 2020. The study uses R- studio software and various econometrics tools and techniques such as descriptive statistics, ANOVA, and CAPM model, and also the study use the GARCH model for the valuation of volatility. The analysis indicates that anticipated volatility remains elevated, potentially leading to more pronounced declines in the stock market. Liu et al. (2021) examine the influence of high-frequency data on the prediction of volatility in the Chinese stock market. The study highlights the significance of utilising intraday data to more precisely measure market volatility compared to conventional daily or lower-frequency data. Through the utilisation of high-frequency data, the authors showcase that realised volatility models, which make use of intraday price variations, provide substantial enhancements in the accuracy of predicting. The results demonstrate that high-frequency data provides a more accurate representation of current market conditions and aids in forecasting short-term changes in volatility, especially in a rapidly changing market such as China. The study highlights the increasing importance of advanced data analytics in financial forecasting. Muşetescu et al., (2022) investigate the utilisation of GARCH models for estimating and predicting the volatility of crude oil prices. Accurate forecasting of volatility is crucial for risk management and strategic decision-making in the oil market, which is highly influenced by geopolitical events, supply-demand changes, and macroeconomic considerations. The paper examines different variations of GARCH models, emphasising their capacity to accurately represent changing patterns of volatility across time. The authors conclude that GARCH models, namely those that consider asymmetric volatility, offer dependable estimates of crude oil price volatility. The paper also evaluates the effectiveness of GARCH in comparison to other econometric models and highlights its appropriateness in markets characterised by frequent volatility clustering, such as the crude oil market. Their research highlights the need of employing GARCH-based models to enhance risk evaluation and make well-informed trading strategies in the highly unpredictable energy sector. Liu et al., (2023) investigate the correlation between trade volume and realised volatility for predicting stock market changes in China. The study investigates the potential of trade volume, which is commonly seen as an indicator of investor sentiment and market liquidity, to enhance the precision of realised volatility forecasts that depend on high-frequency price data. Their empirical research indicates that including trade volume in volatility models greatly improves the accuracy of forecasting, particularly in capturing sudden increases in short-term volatility. The study emphasises the distinct characteristics of the Chinese stock market, where significant changes in prices are often preceded by a large volume of trade. This study offers useful insights into the significance of trading activity as an extra element in models that predict volatility. It highlights the importance of trading activity for investors and risk managers in making well-informed decisions in emerging markets such as China. Song et al. (2023) investigate a novel method for predicting volatility by integrating macroeconomic factors into stock market models through the use of GARCH-MIDAS and deep learning methodologies. The GARCH-MIDAS model is used to combine high-frequency financial data with low-frequency macroeconomic indices, such as GDP, inflation, and interest rates. This combination enables the capture of both transient market volatility and enduring economic trends. In addition, deep learning models are utilised to improve the precision of volatility forecasts by identifying intricate nonlinear patterns in the data. The study's results demonstrate that the integration of conventional econometric models with deep learning techniques greatly enhances the accuracy of forecasting.

**Objective of the Study**

The study tries to reach the following objectives:

I. To investigate the various asymmetric effects of the New York Stock Exchange (NYSE) and the London Stock Exchange (LSE).

II. To determine the presence of leverage effect

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## Data and Study Periods

The study uses secondary sources of time series daily closing data of the New York Stock Exchange (NYSE) and the London Stock Exchange (LSE). The daily data is sourced from the official website of the NSYE and LSE for the period 1st April 2014 to 31st March 2024.

## Methodology

The study employs different statistical approaches, including ARCH model and GARCH family models, which are evaluated through the E-Views econometrics program. Volatility was assessed based on returns; hence, prior to conducting these experiments, daily returns were determined. The logarithm rate of the first difference of daily closing prices both indices NYSE and LSE indices as follows:

$$R_t = \log \frac{P_t}{P_{t-1}} \quad (1)$$

$R_t$ is represents the logarithmic daily return on the NYSE and LSE index at time t, where $P_t$ denotes the closing price at time t and $P_{t-1}$ signifies the comparable price at time t-1.

***Test for Autoregressive Conditional Heteroscedasticity (ARCH) models:***

Examining the residuals for signs of heteroscedasticity is one of the most crucial steps before using the Garch approach. The Lagrange Multiplier test (LM-test) for Autoregressive Conditional Heteroscedasticity(ARCH) is employed to assess the presence of heteroscedasticity in the residuals of the return series. The Autoregressive Conditional Heteroskedasticity (ARCH) model, introduced by Engle (1982), addresses the temporal variability of volatility. In the ARCH model, heteroskedasticity, or non-constant variance, lacks an autoregressive structure. This indicates that the observed heteroskedasticity across several periods is correlated, signifying the existence of the ARCH effect and volatility clustering in time series data. To evaluate the ARCH of the subsequent equation.

$$u_t^2 = \gamma_0 = \gamma_1 u_{t-1}^2 + \gamma_2 u_{t-2}^2 + \ldots + \gamma_p u_{t-p}^2 + v_t \quad (2)$$

Here, the variance of u at time t is ascertained by the squared residual, which the basic regression model can quantify. Delays in 'p' are incorporated in a secondary regression model, however. The equation denotes the ARCH model of order p. The presence of the ARCH effect is determined by testing the validity of the null hypothesis.

$$H_0 = \gamma_0 = \gamma_1 = \gamma_2 = \gamma_p = 0 \quad (3)$$

***Generalized Autoregressive Conditional Heteroskedastic (GARCH) models:***

The Garch model is the main techniques for the measurement of volatility of the stock market. The GARCH model is an extended variant of the ARCH model. Bollerslev introduce the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models in 1986. The study consist the GARCH family model for modelling conditional volatility, whereas EGARCH (1,1) and TGARCH (1,1) were adopted for modelling asymmetric volatility. The application of the GARCH model has become the standard method for modelling volatility in time series data. The mean equation of a GARCH (1, 1) model:

$$R_t = c + \beta R_{t-1} + \varepsilon_t \quad (4)$$

And the variance equation is:

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$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{5}$$

Where ω is a constant, in the term represents ARCH, and the term denotes GARCH. Denotes the influence of recent news (shocks), while β signifies the effect of past events (persistence volatility).The aggregate of the ARCH and GARCH coefficients (α + β) approaches one or is less than one, signifying that the volatility shocks exhibit considerable persistence.

***Asymmetry and Leverage effects:***

The primary limitation of symmetric GARCH is its inability to respond asymmetrically to fluctuations in stock returns. Consequently, several models have been developed to address the issue, referred to as asymmetric models, like EGARCH and TGARCH, which are employed to capture asymmetric occurrences. The study includes the EGARCH and TGARCH models to examine the corelationship with asymmetrics and returns. The leverage effect is predicated on the premise that the distribution of stock returns demonstrates significant asymmetry. Negative news is associated with a greater increase in market volatility than positive news, which produces comparable returns. Furthermore, substantial negative innovations lead to increased volatility in comparison to minor ones. To clarify the asymmetry of volatility in speculative prices Black (1976) asserts that a decline in stock prices results in a corresponding reduction in the value of the company's equity.

***The Exponential Generalized Autoregressive Conditional Heteroskedastic (EGARCH) models:***

In 1991, Nelson introduced the Exponential Generalized Autoregressive Conditional Heteroskedastic (EGARCH) model. The model utilises a logarithmic function to denote the conditional variance. One can assess the Leverage effect to determine the ideal model that precisely reflects the symmetries of the Indian Stock Market. We utilise the subsequent equation to assess the EGARCH (1,1) model:

$$In(\sigma^2) = \omega + \beta_1 In(\sigma_{t-1}^2) + \left\{ \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{\pi}{2}} \right\} - \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{6}$$

β denotes the GARCH component, which reflects the impact of the prior period's forecasted variance. The left side denotes the lag of the conditional variance. The coefficient γ is occasionally termed the asymmetry or leverage term. The hypothesis that γ is negative will be employed to assess the existence of leverage effects. The effect is symmetrical when γ is non-zero.

***The Threshold Generalized Autoregressive Conditional Heteroskedastic (TGARCH) models:***

Zakoian introduced the Threshold Generalized Autoregressive Conditional Heteroskedastic (TGARCH) model in 1994. This is an alternate model that allows for asymmetric effects. The TGARCH model is considered the most suitable approach for evaluating the impact of both positive and negative shocks on volatility. Engle and Ng (1993) discovered that negative shocks induce greater volatility than positive shocks of equivalent magnitude. The TGARCH (1, 1) model is expressed using an equation:

$$\sigma_t^2 = \omega + \alpha_1\varepsilon_{t-1}^2 + \gamma d_{t-1}\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \tag{7}$$

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Where $d_{t-1}$ = 1 if $\varepsilon_{t-1} < 0$ and $d_{t-1}$ = 0 otherwise. In this methodology, γ is designated as the asymmetry or leverage effect. In this model, the positive news (εt-1 < 0) and the negative news (εt-1 < 0) have distinct impacts on the conditional variance. In this model, α denotes the ARCH component while β signifies the GARCH component. Consequently, if γ is substantial and affirmative, negative shocks will exert a more pronounced effect than positive shocks.

## Results & Analysis

### Graphical Presentation of Volatility Clustering of NYSE and LSE

The figures depict the daily returns of the NYSE and LSE indices from 1st April 2014 to 31st March 2024. The graph offers valuable understanding of the significant instability observed in the present timeframe. The volatility clustering is examined by plotting the daily returns of the NYSE and LSE indices. Figures 1 and 2 represent that the daily returns of both the NYSE and LSE indices.

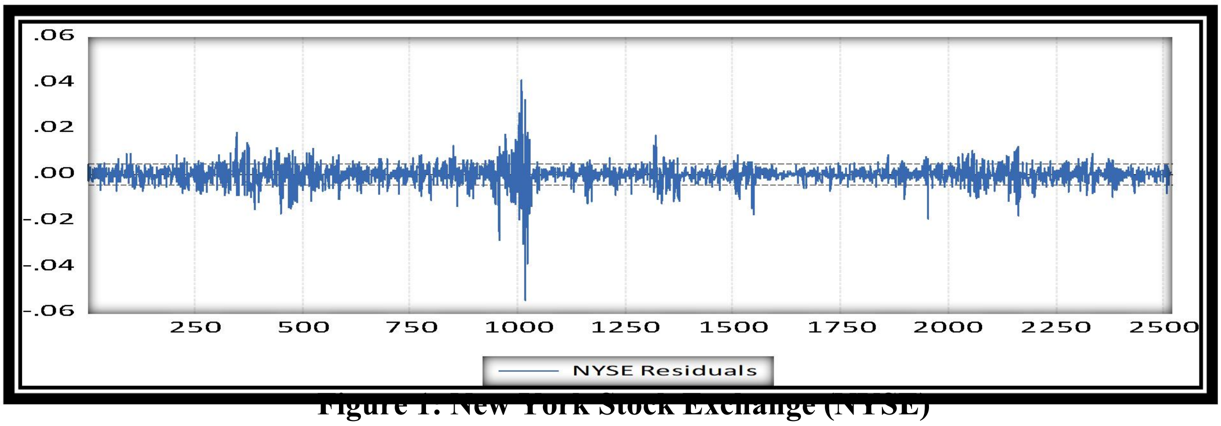


**Figure 1: New York Stock Exchange (NYSE)**

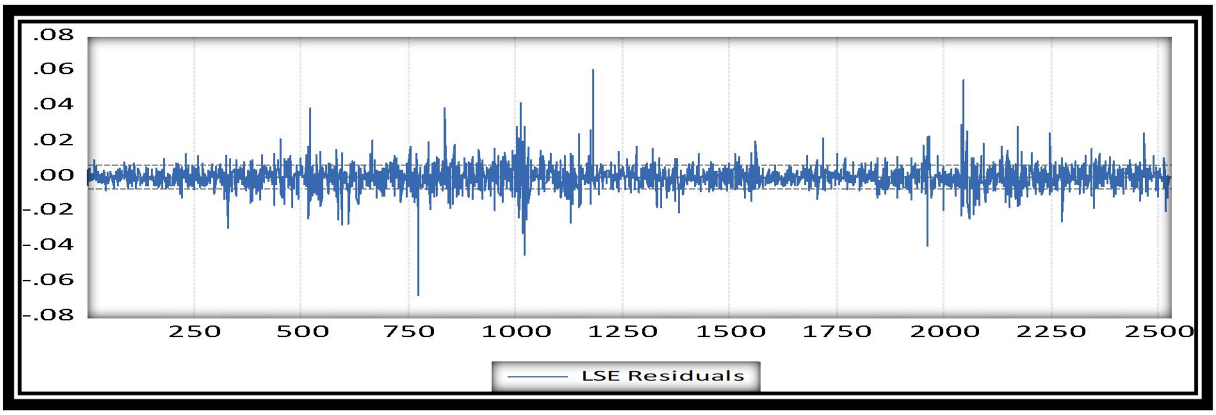


**Figure 2: London Stock Exchange (LSE)**

In the Table 1 shows the descriptive statistics of both the indices NYSE and LSE. The average return and level of risk associated with the NYSE index exceed those of the LSE. The LSE index exhibits negative skewness, indicating a longer left tail in comparison to the right tail. The indices exhibit a kurtosis value below 3, indicating the presence of heavy tails in their distribution. Additionally, the returns series of the indices demonstrate leptokurtic characteristics. In addition, JB test statistics for returns distribution of both market are extremely high, and the probabilities of obtaining such statistics assuming normality are significantly close to zero (at the 99% confidence level). This confirms the rejection of the null hypothesis ($H_0$: Normally distributed).

**Table 1: "Descriptive Statistics"**

| Index | OB | Mean | Median | Max | Min | Std. Dev | Skew | Kurt | JB | P-Value |
|---|---|---|---|---|---|---|---|---|---|---|
| **NYSE** | 2516 | 4.1102 | 4.1033 | 4.2627 | 3.9433 | 0.0734 | 0.1824 | 1.8271 | 158.1589 | 0.0000 |
| **LSE** | 2525 | 3.6793 | 3.6795 | 3.9960 | 3.2105 | 0.2288 | -0.3508 | 1.6782 | 235.5970 | 0.0000 |

Table 2 shows that the F-statistics and LM statistics (533.9534, 440.7024, and 86.5745, 83.7665 respectively) for the NYSE and LSE indexes are statistically significant, indicating the presence of an ARCH effect in the returns. Ultimately, this outcome is validated by the Q-statistics, which is significant in all instances, indicating the presence of ARCH effect and leading to the estimation of GARCH effect.

**Table 2: "ARCH-LM test for ARCH effect of the NYSE and LSE"**

| "Heteroskedasticity Test: ARCH" | | | | | | | |
|---|---|---|---|---|---|---|---|
| NYSE | | | | LSE | | | |
| **'*F*-statistic'** | 533.9534 | **'Prob. *F*(1,2512)'** | 0.0000 | **'*F*-statistic'** | 86.5745 | **'Prob. F(1,2521)'** | 0.0000 |
| **'Obs*$R$-squared'** | 440.7024 | **'Prob. Chi-square(1)'** | 0.0000 | **'Obs*$R$-squared'** | 83.7665 | **'Prob. Chi-Square(1)'** | 0.0000 |

The positive and statistically significant 'β', as shown in Tables 3 and 4, provides clear evidence of the presence of the GARCH effect in the New York Stock Exchange (NYSE) and the London Stock Exchange (LSE). The fluctuations of the both indices are found to be influenced by the introduction of fresh information. The equation for conditional variance involves the coefficients 'α' and 'β', which represent the impact of new information. The coefficient 'α' is statistically significant, suggesting that the current news has a considerable impact on the volatility of the stock market. Similarly, the 'β' coefficient is statistically significant and indicates that the stock market volatility is being influenced by past news. Therefore, the null hypothesis is refuted, and the alternative hypothesis is validated. Taken the statistical significance of 'α' and 'β' coefficients, it is possible to make predictions about future stock prices.

**Table 3: "Estimation of GARCH (1, 1) model for NYSE"**

| "GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)" | | | | |
|---|---|---|---|---|
| **Variable** | **Coefficient** | **Std-Error** | **Z-Statistic** | **Prob.** |
| **'C'** | 5.27E-07 | 8.19E-08 | 6.430629 | 0.0000 |
| **'RESID(-1)^2'** | 0.217123 | 0.019837 | 10.94544 | 0.0000 |
| **'GARCH(-1)'** | 0.768370 | 0.017767 | 43.24741 | 0.0000 |

Table 4: " Estimation of GARCH (1, 1) model for LSE"

| "GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)" | | | | |
|---|---|---|---|---|
| **Variable** | **Coefficient** | **Std-Error** | **Z-Statistic** | **Prob.** |
| **'C'** | 6.07E-06 | 5.61E-07 | 10.81351 | 0.0000 |
| **'RESID(-1)^2'** | 0.254847 | 0.016248 | 15.68514 | 0.0000 |
| **'GARCH(-1)'** | 0.630718 | 0.020579 | 30.64827 | 0.0000 |

To examine the leverage effect, EGARCH model is employed and the result is shown in tables 5 and 6 respectively. Tables 5 and 6 demonstrate a statistically significant asymmetric impact ($\gamma$) of news in the test, with both $\alpha$ and $\beta$ being significant. Therefore, both outdated news and the most recent news are influencing the stock market. Positive news stimulates an upward trend in stock prices, whereas negative news triggers a decline in stock prices. The coefficient '$\gamma$' is positive, greater than zero, and statistically significant at the 1% level. The data indicates that stock prices rise as a result of positive news entering the market, and this has a mitigating effect on market volatility.

Table 5: "Estimation of EGARCH (1, 1) model for NYSE"

| "LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5) *RESID (-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))" | | | | |
|---|---|---|---|---|
| **Variable** | **Coefficient** | **Std-Error** | **Z-Statistic** | **Prob.** |
| **'C(3)'** | -0.309556 | 0.040813 | -7.584794 | 0.0000 |
| **'C(4)'** | 0.203907 | 0.018249 | 11.17347 | 0.0000 |
| **'C(5)'** | 0.202942 | 0.012023 | 16.87905 | 0.0000 |
| **'C(6)'** | 0.985783 | 0.003034 | 324.8640 | 0.0000 |

Table 6: "Estimation of EGARCH (1, 1) model for LSE"

| "LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5) *RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))" | | | | |
|---|---|---|---|---|
| **Variable** | **Coefficient** | **Std-Error** | **Z-Statistic** | **Prob.** |
| **'C(3)'** | -1.047672 | 0.105753 | -9.906783 | 0.0000 |
| **'C(4)'** | 0.341352 | 0.015438 | 22.11159 | 0.0000 |
| **'C(5)'** | 0.068011 | 0.012096 | 5.622586 | 0.0000 |
| **'C(6)'** | 0.921538 | 0.009754 | 94.47959 | 0.0000 |

Table 7 and 8 present the predicted outcomes of the TGARCH (1, 1) model. The coefficient of leverage effect '$\gamma$' is shown to be positive and significant that indicates negative shocks or unfavourable news have a larger impact on the variance compared to good news or positive shocks. Similarly, the '$\beta$' coefficient is statistically significant and indicates that the volatility of the stock market is also being influenced by previous news. The coefficient '$\gamma$' is positive and bigger than zero, indicating that the impact is asymmetric. Any negative news in the stock market triggers greater volatility than positive news.

**Table 7: “Estimation of TGARCH (1, 1) model for NYSE”**

| “GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1) ^2*(RESID(-1)<0) + C(6)*GARCH(-1)” | | | | |
|---|---|---|---|---|
| **Variable** | **Coefficient** | **Std-Error** | ***z*-Statistic** | **Prob.** |
| **‘C’** | 1.75E-07 | 3.98E-08 | 4.401227 | 0.0000 |
| **‘RESID(-1)^2’** | 0.332170 | 0.025621 | 12.96451 | 0.0000 |
| **‘RESID(-1)^2*(RESID(1-)<0)’** | -0.338084 | 0.026037 | -12.98487 | 0.0000 |
| **‘GARCH(-1)’** | 0.865344 | 0.009926 | 87.18198 | 0.0000 |

**Table 8: “Estimation of TGARCH (1, 1) model for LSE”**

| “GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*RESID(-1) ^2*(RESID(-1)<0) + C(6)*GARCH(-1)” | | | | |
|---|---|---|---|---|
| **Variable** | **Coefficient** | **Std-Error** | **z-Statistic** | **Prob.** |
| **‘C’** | 6.40E-06 | 6.17E-07 | 10.38040 | 0.0000 |
| **‘RESID(-1)^2’** | 0.348637 | 0.030198 | 11.54511 | 0.0000 |
| **‘RESID(-1)^2*(RESID(-1)<0)’** | -0.172482 | 0.033865 | -5.093284 | 0.0000 |
| **‘GARCH(-1)’** | 0.620219 | 0.022889 | 27.09730 | 0.0000 |

The forecast error statistics for each model are contingent upon their capacity to anticipate future returns. Various methodologies are employed to assess and choose the most effective forecasting model. The root mean squared error (RMSE) is the predominant metric used. Additionally, there are less widely used metrics such as mean absolute error (MAE), mean absolute percent error (MAPE), and theil inequality coefficient (TIC).

Table 9 reveals the comparison of various models. The GARCH measure is the most effective model for anticipating volatility in both the indices. However, when employing TIC, the GARCH measure demonstrates superior performance for NYSE as it yields the lowest TIC value and In the LSE all the metric is same in all models as it yields the lowest TIC value. However, the TIC metric is not widely used, thus we do not take it into consideration in this context.

**Table 9: “Comparison of (out-of sample) dynamic forecast performance measure”**

| Index | Model | RMSE | MAE | MAPE | TIC |
|---|---|---|---|---|---|
| **NYSE** | **GARCH** | 0.004664 | 0.003015 | 0.073491 | 0.000567 |
| | **EGARCH** | 0.004679 | 0.003024 | 0.073698 | 0.000569 |
| | **TGARCH** | 0.004675 | 0.003021 | 0.073637 | 0.000569 |
| **LSE** | **GARCH** | 0.007061 | 0.004786 | 0.130556 | 0.000958 |
| | **EGARCH** | 0.007063 | 0.004790 | 0.130688 | 0.000958 |
| | **TGARCH** | 0.007064 | 0.004789 | 0.130649 | 0.000958 |

## Conclusion & Recommendation

This study examines volatility predictions on the NYSE and LSE utilising symmetric and asymmetric GARCH models for a period of April 1, 2014 to March 31, 2024. The GARCH (1,1), EGARCH (1,1), and TGARCH (1,1) models are utilised in the analysis following the validation of volatility clustering and the ARCH effect. The GARCH coefficient signifies that the present returns of the indices monitored by the EGARCH measure are affected by past volatility. According to the EGARCH measure, the returns of the indices are not influenced by the leverage effect, suggesting that positive fluctuations are less significant than negative fluctuations. In contrast, the TGARCH metric indicates that adverse news results in elevated conditional volatilities. Asymmetric shocks are evident in the returns of NYSE indices, and these shocks persist over extended durations. The TARCH metric indicates the presence of a leverage impact in the indexes. The standardised residual series of the NYSE index is independently and identically distributed (i.i.d.), whereas the standardised residual series of the LSE is not independently and identically distributed (i.i.d.). Ultimately, the GARCH model is determined to be the most effective forecasting tool for both the NYSE and LSE indices. Therefore, it is advisable to utilise alternative measures for volatility modelling beyond GARCH, EGARCH, and TARCH, which would yield varied outcomes.

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