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Evaluating the Efficacy of GARCH Models in Forecasting Volatility Dynamics Across Major Global Financial Indices: A Decade-long Analysis

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Author's contribution

The sole author designed, analysed, interpreted and prepared the manuscript.

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ABSTRACT

This study investigates the volatility dynamics of five major global financial indices—FTSE 100, Hang Seng, NIKKEI 225, NSE 50, and S&P 500—using a range of GARCH models over a ten-year period from January 1, 2014, to December 31, 2023. The analysis involves preprocessing the data to ensure stationarity, calculating log returns, and conducting stationarity and ARCH effect LM tests. Various GARCH models, including GARCH (0,1), GARCH (1,1), GARCH (1,2), and GARCH (2,2), are applied to capture and forecast volatility. The study aims to determine the most effective model for accurately reflecting volatility dynamics while accounting for significant market events such as the COVID-19 pandemic.

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The findings reveal that the GARCH (1,1) model generally provides a robust balance between model simplicity and statistical significance, effectively capturing the time-varying volatility of the indices. Despite some complex models offering better fit measures according to the Akaike Information Criterion (AIC) and Schwarz Criterion (SC), the GARCH (1,1) model consistently demonstrates significant parameter estimates and reliable predictive performance, as evidenced by consistent Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values. This suggests that the GARCH (1,1) model is a preferred choice for volatility forecasting due to its effectiveness and parsimony, although future research might explore more advanced GARCH model variations for further refinement.

Keywords: ARCH model; GARCH models; global stock indexes; volatility.

1. INTRODUCTION

The accurate prediction of financial market volatility is a cornerstone of modern financial economics, driven by its pivotal role in risk management, portfolio optimization, and strategic decision-making. Volatility, which quantifies the degree of variation in asset prices over time, serves as a critical indicator of market uncertainty and potential risk exposure. Consequently, understanding and forecasting this volatility is of paramount importance to investors, policymakers, and financial institutions. Among the various methods developed to model and predict volatility, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, introduced by Bollerslev in 1986, stands out as a fundamental tool in capturing the intricate dynamics of time-varying volatility. The GARCH model, an extension of the Autoregressive Conditional Heteroskedasticity (ARCH) model proposed by Engle in 1982, has proven particularly effective in addressing the volatility clustering phenomenon frequently observed in financial time series data.

Over the years, GARCH models have evolved into a versatile family of models, each designed to capture specific characteristics of financial markets. These include the Exponential GARCH (EGARCH) model by Nelson [1], which accounts for asymmetric effects of shocks on volatility, and the Threshold GARCH (TGARCH) model by Zakoian [2], which models threshold effects in volatility. Empirical research has demonstrated the robustness of these models across diverse financial markets and economic scenarios, from traditional stock and bond markets to more volatile environments such as cryptocurrency and commodity markets. For instance, studies have shown that GARCH models are particularly adept at capturing the effects of major global events, including financial crises and pandemics, on market behavior. This adaptability makes GARCH models invaluable tools for financial analysts seeking to navigate the complexities of modern financial systems.

Each GARCH model offers unique characteristics tailored to specific aspects of volatility modelling. The basic GARCH (1,1) model is the most widely used due to its simplicity and ability to capture the essential features of financial time series, such as volatility clustering. It balances parsimony and effectiveness, making it ideal for general applications. The GARCH (1,2) and GARCH (2,2) models, with their additional lag terms, provide more flexibility in modelling complex volatility dynamics, potentially offering better fit for time series with longer memory effects or more intricate patterns of volatility persistence. These models can capture more subtle shifts in volatility over time, which might be critical for accurately modelling markets with more erratic behaviour. On the other hand, the GARCH (0,1) model, though less common, is sometimes used to model cases where only the moving average component of volatility is significant. Each of these models caters to different market conditions and data characteristics, allowing researchers to choose the model that best fits the specific volatility patterns of the asset or index under study.

Need for this study lies in the critical role that accurate volatility forecasting plays in financial decision-making, risk management, and policy formulation. By rigorously evaluating the efficacy of various GARCH models across major global financial indices, this research provides valuable insights into the most effective tools for capturing the time-varying nature of market volatility. Such insights are essential for investors, financial institutions, and policymakers, especially in an era characterized by heightened uncertainty and frequent market disruptions, such as the COVID-19 pandemic. The findings guide stakeholders in selecting robust, statistically sound models that balance complexity and predictive accuracy, ultimately enhancing their ability to navigate and mitigate financial risks.

This study contributes to the extensive literature on GARCH models by focusing on their application to major global financial indices, specifically the FTSE 100, Hang Seng, NIKKEI 225, NSE 50, and S&P 500, over a ten-year period from 2014 to 2023. By systematically evaluating the performance of different GARCH models, including GARCH (0,1), GARCH (1,1), GARCH (1,2), and GARCH (2,2), this research aims to identify the most effective model for capturing and forecasting volatility in these indices. The findings are expected to provide crucial insights into the suitability of various GARCH models for different economic environments, thereby offering valuable guidance for both academic researchers and practitioners in the field of financial econometrics.

2. LITERATURE REVIEW

In the expansive realm of financial modelling, the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model and its variants have emerged as fundamental tools for analysing and forecasting volatility across diverse economic landscapes. This narrative synthesis explores a wealth of research studies, each elucidating the nuances and applications of GARCH models in various contexts, from stock markets to commodity prices, and from macroeconomic impacts to unique industry-specific challenges.

The study of financial market volatility has been a cornerstone of financial econometrics, particularly through the development and application of various autoregressive conditional heteroskedasticity (ARCH) models. Bollerslev [3] pioneered this area by introducing the generalized autoregressive conditional heteroskedasticity (GARCH) model, extending the basic ARCH framework to incorporate past conditional variances. This model set the stage for a plethora of GARCH-type models that aim to capture the complex dynamics of financial time series data. Among the early extensions of the GARCH model, Nelson [1] introduced the exponential GARCH (EGARCH) model, which accommodates the asymmetric effects of shocks on volatility. The EGARCH model, along with others like the GJR model by Glosten et al. [4] and the NGARCH model by Bera and Higgins [5], have been instrumental in understanding financial volatility. These models address the need to capture volatility asymmetry, a common feature in financial markets where negative shocks often have a larger impact on volatility than positive ones.

Further advancements include the Asymmetric Power GARCH model by Ding et al. [6] and the Threshold GARCH model by Zakoian [2], which refine the ability to model asymmetries and threshold effects in volatility. Bollerslev and Ghysels [7] introduced the periodic GARCH (PGARCH) model, which accounts for seasonal volatility patterns in high-frequency asset returns. These models have significantly improved our understanding of volatility dynamics, providing better tools for risk management and forecasting. Empirical studies across different markets and time periods have demonstrated the utility of these models. Rossetti et al. [8] examined fixed income market volatility in 11 countries, focusing on interbank interest rates from January 2000 to December 2011. Their study employed an array of models, with the EGARCH model emerging as particularly adept at capturing volatility influenced more by internal macroeconomic events than external shocks. Similarly, Chkili et al. [9] investigated Islamic stock market volatility from 1999 to 2017, encompassing pivotal events like the 9/11 attacks and the 2008 financial crisis. They introduced a hybrid model combining FIAPARCH and artificial neural networks (ANN), which outperformed traditional models in forecasting accuracy.

Paolella et al. [10] delved into the implications of carbon and sulphur dioxide emission allowances on global power and gas markets. Their focus on the U.S. Clean Air Act and the EU Emissions Trading Scheme highlighted the crucial role of understanding statistical distributions and forecast abilities of emission trading returns for optimal hedging and purchasing strategies. On a different note, Evgenidis et al. [11] explored the predictive power of the yield spread on real economic growth by examining its relationship with interest rate volatility through GARCH models and Markov regime switching. In the realm of reliability forecasting, Liang [12] introduced the GARCH model to analyze and forecast failure data for repairable systems, specifically electronic systems from Chrysler suppliers. This innovative application demonstrated the model's effectiveness in analysing failure data volatility and predicting future failures. Arthur et al. (1996) presented a theory of asset pricing based on heterogeneous agents who adapt their expectations to market dynamics. Through computational experiments with an artificial stock market, they showcased how the evolution of traders' expectations leads to various market regimes.

Banking sector studies by Elyasiani [13] utilized a multivariate GARCH model to analyze bank stock returns and their volatilities in response to short-term and long-term interest rates across three portfolios: money centre banks, large banks, and small banks. Yang et al. [14] evaluated financial market risk in the digital economy using a GARCH-VaR model tailored for big data, underscoring the increasing complexity of modern financial markets. Rehman et al. [15] examined the effects of the 2008 Global Financial Crisis and the COVID-19 pandemic on stock markets in six GCC economies using ARCH/GARCH models, revealing significant impacts on market behaviour. Bitcoin's potential as an alternative to fiat currencies was assessed by Cermak [16], who analysed its volatility using a GARCH(1,1) model in relation to macroeconomic variables. Handika et al. (2016) evaluated the accuracy of various volatility models through a Value-at-Risk (VaR) approach, examining their impact on investment performance in financialized commodity markets. Rastogi et al. [17] explored the volatility of agricultural commodity prices and their impact on inflation in India using BEKK GARCH and DCC GARCH models, highlighting the intricate interplay between commodity markets and macroeconomic indicators.

Lim et al. [18] modelled the volatility of Malaysia's stock market using symmetric and asymmetric GARCH models, comparing their performance across different time frames from 1990 to 2010. Arsalan et al. [19] analysed stock market volatility and mean reversion across various global stock exchanges using the GARCH(1,1) model, providing insights into international market dynamics. Onali [20] studied the impact of COVID-19 cases and deaths on the US stock market using a GARCH(1,1) model, highlighting the pandemic's profound effect on financial markets. In a comprehensive analysis, Mobin et al. [21] investigated the impact of COVID-19 on the risk dynamics of stock and bond markets in G7 countries using GARCH models, revealing shifts in market risk profiles. Liu et al. [22] developed a BTC trading prediction model by integrating DCC-GARCH and artificial neural networks (ANN), leveraging dynamic correlation and volatility data to enhance trading strategies. Abbas et al. [23] examined the interaction between macroeconomic uncertainty and stock market return and volatility in China and the USA using GARCH models and a multivariate VAR model.

Guo [24] investigated the economic significance of predicting foreign exchange rate volatility using GARCH models versus implied volatility from currency options. Debasish [25] explored the impact of Nifty index futures on the volatility of Indian spot markets using econometric models, providing insights into derivative markets. Al-Rjoub et al. [26] examined stock returns and volatility during financial crises in Jordan using the GARCH-M model, shedding light on market behavior during turbulent periods. Mahmoud Sayed Agbo [27] forecasted prices of key Egyptian export crops using ARIMA and GARCH models, emphasizing the importance of volatility modelling in agricultural markets. Hartz et al. [28] demonstrated that using non-Gaussian innovation distributions in GARCH models is more effective for capturing volatility clustering and improving value-at-risk predictions compared to outlier removal. Badaye et al. [29] introduced a novel methodology using MC-GARCH and copula models to forecast intraday VaR and ES for foreign currency portfolios.

Setiawan et al. [30] examined the impact of the COVID-19 pandemic on stock market returns and volatility in Indonesia and Hungary using a GARCH(1,1) model, highlighting the pandemic's disparate effects on emerging and developed economies. Lee et al. [31] proposed an orthogonal ARMA-GARCH approach for generating economic scenarios to manage risks in financial institutions, especially during turbulent periods like the COVID-19 pandemic. Rajvanshi et al. [32] evaluated the forecasting power of GARCH models for the Nifty 50 index's return volatility using realized volatility as a proxy. Dixit et al. [33] evaluated the informational efficiency of S&P CNX Nifty index options in India, providing insights into derivative market dynamics.

Sreenu et al. [34] examined the impact of volatility on asset pricing and financial risk in the Indian stock market using GARCH-M and E-GARCH-M models, highlighting the complex relationship between volatility and asset pricing. Duppati et al. [35] examined the ability of intraday data to predict long-term memory in volatility for Asian equity indices using GARCH-based models and realized volatility approaches.

Flannery [36] estimated a GARCH model to analyze how daily equity returns and their volatility are influenced by macroeconomic variables, providing a comprehensive view of market dynamics. Ugurlu et al. [37] evaluated GARCH-type models for stock market volatility in European emerging countries and Turkey, using daily data to offer insights into regional market behaviour. Kinateder et al. [38] integrated long memory with a GARCH(1,1) model and fat-tailed innovations to forecast market risk over multiple periods, enhancing risk management strategies.

Chen [39] investigated the changing risk-return relationship in Chinese stock markets, focusing on differences between Shanghai and Shenzhen, varying data frequencies, and comparing GARCH-M model specifications. Abrosimova et al. [40] tested weak-form efficiency in the Russian stock market using various data frequencies, providing insights into market efficiency. Naidoo et al. [41] examined how exchange rate volatility affects South Africa's stock and real estate markets using GARCH(1,1) models, highlighting the interconnectedness of financial markets. Handika et al. [42] examined the empirical performance of GARCH models in forecasting volatility across financialized commodity markets, demonstrating the model's robustness. Mușetescu et al. [43] used GARCH(1,1), GARCH-M(1,1), and EGARCH(1,1) models to estimate and predict Brent Crude Oil return volatility, emphasizing the importance of accurate volatility modelling in energy markets. Rastogi et al. [44] explored the volatility spillover effects of crude oil, gold, interest rates, and exchange rates on inflation in India using BEKK-GARCH and DCC-GARCH models.

Amelot et al. (2020) evaluated time series models, artificial neural networks (ANNs), and statistical topologies to forecast foreign exchange rates, providing a comparative analysis of forecasting methodologies. Wang et al. [45] used a GARCH model with structural breaks to forecast stock volatility in the Chinese stock market, incorporating financial news sentiment analysis to enhance predictive accuracy. Wu [46] developed a threshold GARCH model to analyze and predict long-term volatility, highlighting the model's sensitivity to different volatility regimes. Xie et al. [47] used the MIDAS-GARCH model to integrate mixed-frequency investor sentiment into stock volatility forecasting, showcasing its superior explanatory power over traditional models. In conclusion, the vast array of studies utilizing GARCH models underscores their critical role in understanding and forecasting volatility across diverse financial contexts. From stock markets to commodity prices, and from macroeconomic impacts to specific industry challenges, GARCH models provide a robust framework for capturing the intricate dynamics of volatility. These models' adaptability and predictive power make them indispensable tools for financial analysts, economists, and policymakers seeking to navigate the complexities of modern financial markets.

3. METHODOLOGY

The study will utilize daily closing prices of the FTSE 100, Hang Seng, NIKKEI 225, NSE 50, and S&P 500 indexes. These indexes were selected due to their representation of major global economies and their significance in financial markets. The data will be obtained from reliable financial databases, specifically Yahoo Finance, covering a period of ten years, from January 1, 2014, to December 31, 2023. This extensive time span ensures a comprehensive analysis that includes various market conditions, such as bull and bear markets, periods of economic stability, and the effects of significant events like the COVID-19 pandemic. By capturing the full spectrum of volatility dynamics, this study aims to provide a nuanced understanding of the predictive capabilities of ARCH/GARCH models in the context of global financial indexes.

Each GARCH model offers unique characteristics tailored to specific aspects of volatility modelling. The basic GARCH (1,1) model is the most widely used due to its simplicity and ability to capture the essential features of financial time series, such as volatility clustering. It balances parsimony and effectiveness, making it ideal for general applications. The GARCH (1,2) and GARCH (2,2) models, with their additional lag terms, provide more flexibility in modelling complex volatility dynamics, potentially offering better fit for time series with longer memory effects or more intricate patterns of volatility persistence. These models can capture more subtle shifts in volatility over time, which might be critical for accurately modelling markets with more erratic behaviour. On the other hand, the GARCH (0,1) model, though less common, is sometimes used to model cases where only the moving average component of volatility is significant. Each of these models caters to different market conditions and data characteristics, allowing researchers to choose the model that best fits the specific volatility patterns of the asset or index under study.

Before applying the GARCH models, it is essential to preprocess the collected data to ensure its suitability for analysis. This preprocessing involves several key steps:

3.1 Log Returns Calculation

To facilitate effective volatility modelling, daily log returns will be computed from the closing prices of the indexes. Log returns are preferred over simple returns because they tend to be more stationary, which is crucial for accurate volatility estimation. The log return is calculated using the following formula:

$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right)$, Where p_t and p_{t-1} are the closing prices at time t and t-1

3.2 Basic Descriptive Statistics

Mean, standard deviation, skewness, and kurtosis—will be calculated to gain insights into the characteristics of the log returns. These statistics will help in understanding the central tendency, dispersion, and distribution shape of the data.

3.3 Stationarity Check

The stationarity of the log returns will be assessed using three tests: Augmented Dickey-Fuller (ADF) Test: This test checks for the presence of a unit root in the time series. If the test statistic is less than the critical value at a given confidence level and the p-value is below the chosen significance level, the null hypothesis of a unit root can be rejected, indicating that the series is stationary. Augmented Dickey-Fuller Generalized Least Squares (ADF-GLS) Test: An enhancement of the ADF test, this test also evaluates the presence of a unit root but includes generalized least squares detrending to improve power. Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test: This test examines the null hypothesis of stationarity against the alternative hypothesis of non-stationarity. It determines whether the series is stationary around a trend (trend-stationary) or around a mean (level-stationary).

3.4 ARCH Effect

The ARCH-LM (Autoregressive Conditional Heteroskedasticity - Lagrange Multiplier) test will be employed to detect the presence of autoregressive conditional heteroskedasticity (ARCH) effects in the time series. This test is crucial for identifying whether the variance of the residuals is dependent on past error terms, which is a typical feature in financial time series. The test statistic is compared with critical values from the chi-squared distribution; if the statistic exceeds the critical value, the null hypothesis of no ARCH effects is rejected.

3.5 Visual Analysis

Time series plots of the log returns will be generated to visually inspect the data for patterns, anomalies, and the presence of ARCH effects. This visual inspection helps in identifying trends, cycles, or irregularities that might not be apparent through statistical tests alone.

3.6 Model Specification

The study will utilize several GARCH models to forecast the volatility of the selected stock indexes, incorporating the normal distribution. The analysis will encompass symmetric model, including the GARCH (0,1), GARCH (1,1), GARCH (1,2) and GARCH (2,2).

3.7 ARCH Model

In traditional econometrics, it is commonly assumed that the variance of a random variable is constant over time. However, financial time series often display heteroscedasticity, where variance remains stable over the long term but fluctuates in the short term. To address this time-varying volatility, Engle [48] developed the Autoregressive Conditional Heteroskedasticity (ARCH) model. This model is specifically designed to capture and model the evolving variance and mean of time series data. The general representation of the ARCH model is:

$$y_t = \phi\, x_t + \mu_t \quad (1)$$

$$\sigma_t^2 = E(\mu_t^2 | \mu_{t-1}, \mu_{t-2} \ldots\ldots) = \alpha_0 + \alpha_1\mu_{t-1}^2 + \ldots\ldots\ldots\ldots + \alpha_p\mu_{t-p}^2 = \sum_{i=1}^{p} \alpha_i\mu_{t-i}^2 \quad (2)$$

In the ARCH model, ϕ is a non-zero parameter that needs to be estimated, x_t represents the independent variable observed at time t, and u_t is the random error term, which is typically assumed to follow a normal distribution in the standard model. The core idea of the ARCH model is that the variance of the residuals μ_t at time t depends on the squared error terms from previous periods. Specifically, the model asserts that the variance of the error term at time t is a linear function of the squared error terms from the preceding p periods. However, the ARCH model assumes that both positive and negative shocks impact volatility equally, making it less suitable for analysing time series data with asymmetric effects.

3.8 GARCH Model

Bollerslev [3] introduced an important refinement to the ARCH model known as the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model. This model is designed to better capture the volatility clustering commonly observed in financial time series. Unlike the ARCH model, the GARCH model incorporates the conditional variance as a GARCH process, allowing for more accurate estimation of time-varying volatility. The defining equations of the GARCH model are as follows:

$$y_t = \phi\, x_t + \mu_t\,,\ \mu \sim N(0, \sigma_t^2) \tag{3}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \mu_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{4}$$

In this model, μ_{t-i}^2 represents the ARCH parameter, while σ_{t-i}^2 is the GARCH parameter. The coefficients associated with the ARCH and GARCH terms are indicated by α and β, respectively, and p and q indicate the lag order of the model. Therefore, the ARCH model can be seen as a specific case within the broader GARCH framework. In this study, primarily utilize the GARCH(1,1) model, which includes one lag, to estimate the sample series. The strength of the GARCH model lies in its ability to reflect and interpret heteroscedasticity. However, it still falls short in capturing asymmetry in financial time series.

3.9 Diagnostic Tests

To evaluate the adequacy and predictability of the GARCH models used in this study, several diagnostic tests will be conducted. The Akaike Information Criterion (AIC) and the Schwarz Criterion (SC), also known as the Bayesian Information Criterion (BIC), are utilized to assess model fit while balancing complexity. The AIC helps in selecting models that achieve a good balance between fit and parsimony by penalizing excessive complexity. Similarly, the SC also accounts for the number of parameters but imposes a stricter penalty for model complexity as the sample size increases. Both criteria are instrumental in identifying models that are both accurate and efficient. Additionally, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) will be used to evaluate the predictive accuracy of the models. RMSE measures the average magnitude of prediction errors, providing insight into how well the model predicts the observed data. MAE, on the other hand, calculates the average absolute differences between observed and predicted values, offering a more robust measure of accuracy that is less influenced by outliers. Together, these diagnostic metrics will guide the selection of the most appropriate model for forecasting volatility, ensuring that the chosen model effectively captures the dynamics of the financial time series data [49-54].

4. RESULTS AND DISCUSSION

The results analysis will focus on evaluating the performance of the various GARCH models in forecasting volatility for the selected stock indexes. By comparing the models' predictive accuracy and fit using metrics such as AIC, SC, RMSE, and MAE, the study aims to identify the most effective approach for capturing volatility dynamics. This analysis will provide insights into the relative strengths and weaknesses of each model, guiding future volatility forecasting strategies.

Table 1 provides a comprehensive overview of the descriptive statistics for five major global indexes—FTSE 100, Hang Seng, NIKKEI 225, NSE 50, and S&P 500—over the period from 2014 to 2023. The mean returns of these indexes vary, with the NSE 50 showing the highest average return at 0.05045, followed by the S&P 500 and NIKKEI 225. In contrast, the Hang Seng index exhibits a negative mean return of -0.012707. The median returns across the indexes are generally higher than their means, indicating skewness in the return distributions. For instance, the FTSE 100 and NSE 50 have medians of 0.056513 and 0.07675, respectively, compared to their mean returns, suggesting positive skewness in their return distributions.

Table 1. Descriptive statistics of five global indexes during 2014 to 2023 period

Variable	FTSE 100	HANGSENG	NIKKE I225	NSE 50	S&P 500
Mean	0.0053909	-0.012707	0.029454	0.05045	0.03768
Median	0.056513	0.028185	0.075226	0.07675	0.05972
Minimum	-11.512	-6.5673	-8.2529	-13.904	-12.765
Maximum	8.6668	8.6928	7.7314	8.4003	8.9683
Std. Dev.	1.0004	1.3009	1.2585	1.0485	1.1212
C.V.	185.56	102.38	42.727	20.783	29.757
Skewness	-0.86492	0.070791	-0.1421	-1.3743	-0.8079
Ex. kurtosis	12.828	3.2598	4.2747	20.453	16.041
5% Perc.	-1.5223	-2.1453	-2.0566	-1.5115	-1.6827
95% Perc.	1.4742	2.001	1.9493	1.5095	1.544
IQ range	0.94588	1.3986	1.272	1.046	0.94678

(Source: Statistical calculations)

Table 2. Unit root test of selected international indices returns

Indexes	ADF Test (12 lag)	ADF GLS Test (12 lag)	KPSS Test (8 lag)	ARCH LM Test (5 lag)
FTSE 100	-15.2617* (0.0000)	-11.1424* (0.0000)	0.022667* (>0.1000)	429.598* (0.0000)
HANG SENG	-49.3353* (0.0000)	-49.2632* (0.0000)	0.022667* (>0.1000)	234.640* (0.0000)
NIKKEI 225	-28.7549* (0.0000)	-17.6862* (0.0000)	0.020862* (>0.1000)	223.998* (0.0000)
NIFTY 50	-13.5031* (0.0000)	-10.8833* (0.0000)	0.037368* (>0.1000)	431.221* (0.0000)
S&P 500	-15.7598* (0.0000)	-9.17740* (0.0000)	0.024392* (>0.1000)	913.263* (0.0000)

(Source: Statistical calculations)(5 percent level of significance) (Probabilities in parenthesis)*

The table also reveals significant variability in the indexes, with the Hang Seng index showing the highest standard deviation of 1.3009, indicating greater volatility compared to the other indexes. The coefficient of variation (C.V.), which reflects the relative dispersion of the returns, is notably high for the FTSE 100 at 185.56, suggesting extreme variability in returns relative to its mean. The indexes exhibit varying degrees of skewness and excess kurtosis, with the FTSE 100 and NSE 50 showing pronounced negative skewness and high excess kurtosis, indicating heavy tails and a higher likelihood of extreme return values. Overall, the descriptive statistics highlight the diverse volatility and return characteristics of these global indexes, underscoring the importance of tailored volatility modelling approaches for accurate forecasting.

Table 2 presents the results of unit root and ARCH-LM tests conducted on the returns of selected international indices, including the FTSE 100, Hang Seng, NIKKEI 225, NSE 50, and S&P 500. The results from the Augmented Dickey-Fuller (ADF) and ADF GLS tests, with 12 lags, show that all indices are stationary as indicated by their test statistics being significantly negative and their p-values being well below the 5 percent significance level. This confirms that the returns of these indices do not contain a unit root and are thus appropriate for further analysis. The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test results also support stationarity for all indices, as the test statistics are below the critical value thresholds, confirming that the time series are stationary around a mean.

The ARCH-LM test results reveal significant autoregressive conditional heteroskedasticity (ARCH) effects in the returns of all indices, with high test statistics and p-values well below 0.05. This indicates that the volatility of these indices is not constant over time but instead depends on past squared returns, which aligns with the common observation of volatility clustering in financial time series. The large test statistics suggest that the variance of the returns is significantly influenced by past error terms, justifying the use of GARCH models to analyze, and forecast volatility for these indices. The combination of results from these diagnostic tests confirms that the returns are stationary and exhibit ARCH effects, making them suitable for further volatility modelling using GARCH models.

4.1 Time Series Plot

The Chart 1 shows the daily returns of the FTSE 100 index from 2014 to 2023. The data exhibits significant volatility, with periods of higher fluctuations around 2016 and a notable spike in 2020, likely corresponding to the COVID-19 pandemic's market impact. Post-2020, the volatility seems to stabilize but remains elevated compared to the earlier part of the period. This pattern highlights how major global events can significantly impact financial markets, causing sharp fluctuations in daily returns. The overall trend does not show a clear directional movement, indicating a mix of gains and losses throughout the period.

The daily returns of the Hang Seng Index from 2014 to 2023 (Chart 2) exhibit characteristics typical of ARCH (Autoregressive Conditional Heteroskedasticity) effects, where periods of high volatility are followed by more high volatility and periods of low volatility tend to follow low volatility. The spikes in volatility around 2016 and the significant increase in 2020 highlight this clustering behavior. This clustering effect is indicative of the ARCH process, where the magnitude of returns tends to be auto-correlated. Specifically, the heightened volatility during the COVID-19 pandemic in 2020 and the elevated levels post-2020 demonstrate how past volatility can influence future volatility, resulting in persistent periods of high and low fluctuations. This visual effect underscores the importance of using ARCH or GARCH models to better understand and forecast future volatility based on past patterns in financial time series data like the Hang Seng Index returns.

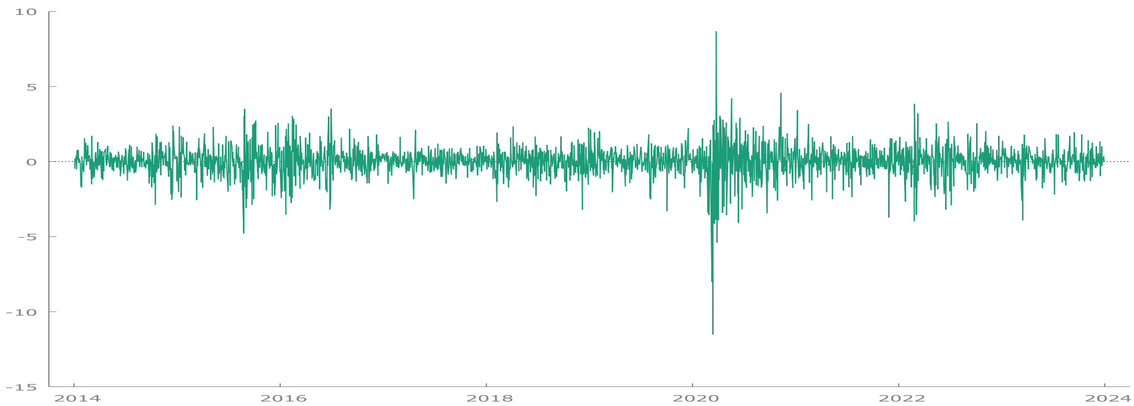

Chart 1. FTSE 100 daily returns from 2014 to 2023
(Source: Statistical calculations)

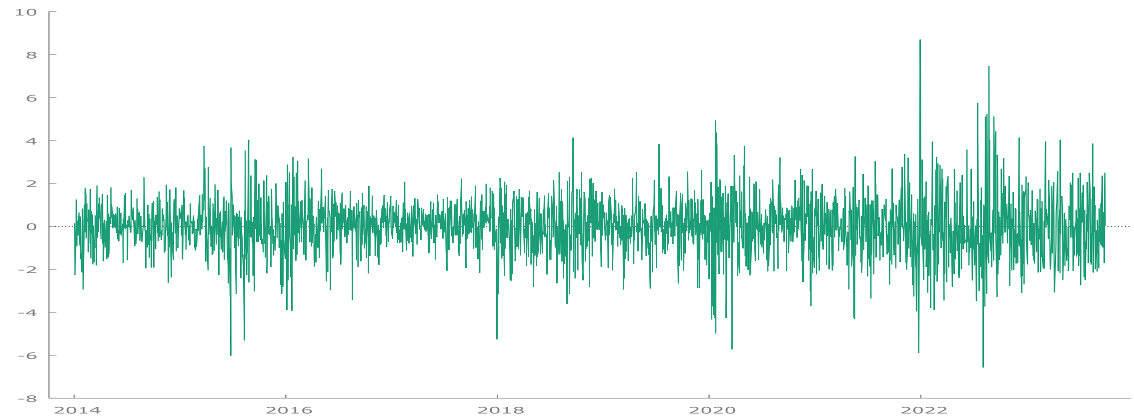

Chart 2. HANG SENG daily returns from 2014 to 2023
(Source: Statistical calculations)

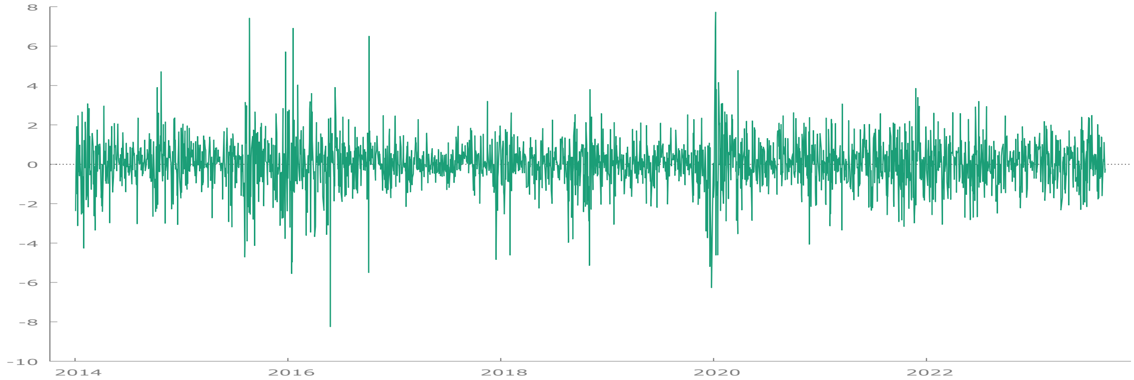

Chart 3. NIKKEI 225 daily returns from 2014 to 2023
(Source: Statistical calculations)

Chart 4. NSE 50 daily returns from 2014 to 2023
(Source: Statistical calculations)

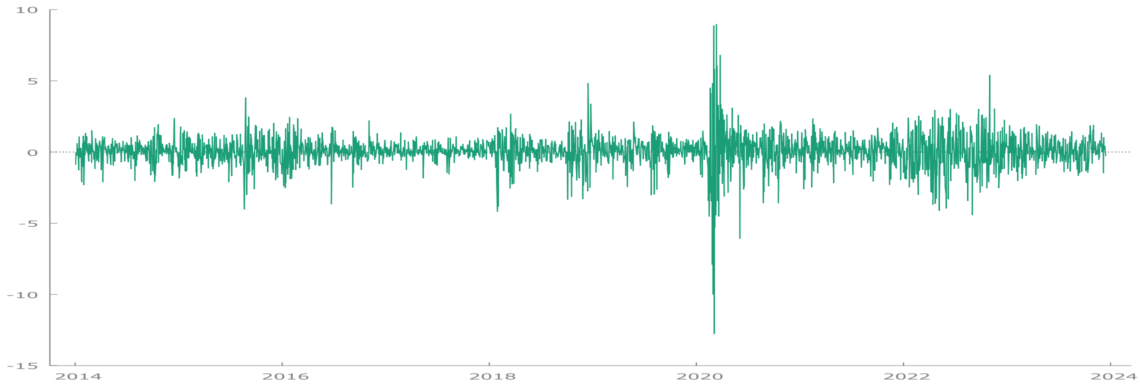

Chart 5. S&P 500 daily returns from 2014 to 2023
(Source: Statistical calculations)

The Chart 3 depicts the daily returns of the Nikkei 225 index from 2014 to 2023, showcasing notable volatility patterns over the period. Observing the chart, there are periods of intense fluctuation around 2016 and a significant spike in 2020, likely due to the global impact of the COVID-19 pandemic. Post-2020, the data shows a continuation of heightened volatility, although with some stabilization compared to the peak. The chart clearly exhibits ARCH (Autoregressive Conditional Heteroskedasticity) effects, where clusters of high volatility follow previous high volatility periods, and similarly, clusters of low volatility follow low volatility periods. This visual clustering suggests that past volatility has a predictive influence on future volatility, making ARCH models particularly useful for analyzing and forecasting the volatility patterns seen in the Nikkei 225 daily returns.

The daily returns (Chart 4) of the NSE 50 Index from 2014 to 2023 display typical characteristics of ARCH (Autoregressive Conditional Heteroskedasticity) effects, where high volatility periods are followed by more high volatility, and low volatility periods follow low volatility. Notable spikes in volatility around 2016 and the significant surge in 2020 highlight this clustering behavior. This pattern is indicative of the ARCH process, where the magnitude of returns tends to be auto-correlated. The heightened volatility during the COVID-19 pandemic in 2020 and the elevated levels of volatility post-2020 demonstrate how past volatility influences future volatility, resulting in persistent periods of fluctuation. This visual effect emphasizes the importance of using ARCH or GARCH models to better understand and forecast future volatility based on past patterns in financial time series data like the NSE 50 Index returns.

The daily returns of the S&P 500 Index from 2014 to 2023 (Chart 5) exhibit characteristics typical of ARCH (Autoregressive Conditional Heteroskedasticity) effects, where periods of high volatility are followed by more high volatility and periods of low volatility tend to follow low volatility. The spikes in volatility around 2016 and the significant increase in 2020 highlight this clustering behavior. This clustering effect is indicative of the ARCH process, where the magnitude of returns tends to be auto-correlated. Specifically, the heightened volatility during the COVID-19 pandemic in 2020 and the elevated levels post-2020 demonstrate how past volatility can influence future volatility, resulting in persistent periods of high and low fluctuations. This visual effect underscores the importance of using ARCH or GARCH models to better understand and forecast future volatility based on past patterns in financial time series data like the S&P 500 Index returns.

The analysis of the daily returns for five major indexes from 2014 to 2023—FTSE 100, Hang Seng, Nikkei 225, NSE 50, and S&P 500—reveals common patterns of volatility influenced by global events, particularly the COVID-19 pandemic in 2020. All five indexes exhibit significant volatility spikes around 2016 and a pronounced surge in 2020, highlighting the impact of global crises on financial markets. Post-2020, while some stabilization is observed, volatility remains elevated compared to the earlier part of the period across all indexes. This persistent volatility underscores the presence of ARCH (Autoregressive Conditional Heteroskedasticity) effects, where periods of high volatility follow high volatility and low volatility follows low volatility, indicating that past volatility influences future fluctuations. This clustering behaviour is evident in the Hang Seng, Nikkei 225, NSE 50, and S&P 500 indexes, with notable periods of heightened volatility during and after the COVID-19 pandemic. The FTSE 100 also shows significant volatility but without a clear directional trend, reflecting a mix of gains and losses. These observations underscore the importance of using ARCH or GARCH models to analyze and forecast future volatility, as they account for the auto-correlated nature of return magnitudes in financial time series data. Understanding these patterns helps in better risk management and strategic decision-making in financial markets.

The Table 3 presents the parameters and performance metrics for various GARCH models applied to the daily returns of five major indices: FTSE 100, Hang Seng (HS), Nikkei 225, NIFTY 50, and S&P 500. For each index, different GARCH models (including GARCH (1,1), GARCH (1,2), and GARCH (2,2)) are evaluated, with specific attention to constants, alpha, and beta coefficients, as well as information criteria and error metrics. The significance of the parameters is indicated by asterisks, denoting statistical significance. For the FTSE 100 index, the GARCH (1,1), GARCH (1,2), and GARCH (2,2) models show varied parameter values. The GARCH (1,1) model has a constant of 0.0268, with significant alpha (0.0553) and beta (0.7857) coefficients. The (1,2) and (2,2) models present more complex structures with additional parameters, leading to slightly different Akaike Information Criterion (AIC) and Schwarz Criterion (SC) values. Notably, the GARCH (2,2) model, despite its complexity, has the lowest AIC (6360.16), indicating it might provide the best fit among the models tested for FTSE 100. The Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values are consistent across models, indicating similar forecasting accuracy.

Table 3. Various GARCH model parameters of global stock index returns

S. No	Index	GARCH Model	Constant	α_0	α_1	α_2	β_1	β_2	AIC	SC	RMSE	MAE
1	**FTSE 100**	(1,1)	0.0268	**0.0553***	**0.1532***		**0.7857***		6364.97	**6394.14**	**1.0004**	0.6769
			(0.0783)	**(0.0000)**	**(0.0230)**		**(0.0000)**					
		(1,2)	0.0455*	0.0647*	0.1674*	0.0000	0.7625*		6369.31	6404.31	1.0010	**0.6765**
			(0.0029)	(0.0000)	(0.0000)	(1.0000)	(0.0000)					
		(2,2)	0.0294	0.0698*	0.2277*	0.0000	0.3091*	0.3959*	**6360.16**	6401.00	1.0004	0.6768
			(0.0518)	(0.0000)	(0.0000)	(1.0000)	(0.0216)	(0.0000)				
2	**HS**	(0,1)	−0.0086	1.4177*	0.1486*				8179.53	8202.76	**1.3007**	0.9435
			(0.7302)	(0.0000)	(0.0000)							
		(1,1)	0.0244	**0.0225***	**0.0619***		**0.9253***		7898.15	**7927.19**	1.3012	**0.9429**
			(0.2717)	**(0.0000)**	**(0.0000)**		**(0.0000)**					
		(1,2)	0.0254	0.0278*	0.0376*	0.0360	0.9108*		**7898.13**	7932.98	1.3012	0.9429
			(0.2489)	(0.0029)	(0.0350)	(0.1489)	(0.0000)					
3	**NIKKEI 225**	(1,1)	**0.0653***	**0.0790***	**0.1257***		**0.8248***		7629.27	**7658.28**	**1.2587**	0.8939
			(0.0021)	**(0.0000)**	**(0.0000)**		**(0.0000)**					
		(1,2)	0.0734*	0.0824*	0.1310*	0.0000	0.8195*		7631.58	7666.39	1.2590	**0.8938**
			(0.0006)	(0.0002)	(0.0000)	(1.0000)	(0.0000)					
		(2,2)	0.0660*	0.1446*	0.1042*	0.1333*	0.0000	0.6722*	**7627.54**	7668.15	1.2587	0.8939
			(0.0018)	(0.0000)	(0.0000)	(0.0000)	(1.0000)	(0.0000)				
4	**NIFTY 50**	(1,1)	**0.0813***	**0.0208***	**0.0916***		**0.8879***		**6364.72**	**6393.74**	**1.0488**	**0.7092**
			(0.0000)	**(0.0000)**	**(0.0000)**		**(0.0000)**					
		(1,2)	0.0812*	0.0211*	0.0865*	0.0062	0.8864*		6366.66	6401.49	1.0488	0.7092
			(0.0000)	(0.0002)	(0.0004)	(0.8154)	(0.0000)					
		(2,2)	0.0803*	0.0383*	0.0729*	0.0912*	0.1377	0.6601*	6366.43	6407.07	1.0488	0.7092
			(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.4096)	(0.0000)				
5	**S&P 500**	(1,1)	**0.0771***	**0.0386***	**0.1988***		**0.7728***		**6396.70**	**6425.85**	1.1217	**0.7245**
			(0.0000)	**(0.0000)**	**(0.0000)**		**(0.0000)**					
		(1,2)	0.0771*	0.0387*	0.1981*	0.0015	0.7720*		6398.70	6433.68	1.1217	0.7245
			(0.0000)	(0.0000)	(0.0000)	(0.9653)	(0.0000)					
		(2,2)	0.0753*	0.0688*	0.1843*	0.1690*	0.0000	0.5958*	6399.84	6440.66	**1.1216**	0.7245
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(1.0000)	(0.0000)				

(Source: Statistical calculations)

For the Hang Seng index, the GARCH (0,1), GARCH (1,1), and GARCH (1,2) models show distinct parameter estimates and model fits. The GARCH (0,1) model has a negative constant, which is not statistically significant, and high alpha (1.4177) and beta (0.1486) coefficients. The GARCH (1,1) model shows improved parameter significance and fit, with an AIC of 7898.15, significantly lower than the (0,1) model's AIC. Both the (1,1) and (1,2) models have nearly identical AIC and SC values, indicating that adding another beta parameter (in (1,2)) does not significantly improve the model fit. The RMSE and MAE values are also similar across these models, indicating consistent predictive performance. The Nikkei 225 index models also show significant parameter estimates for all tested GARCH structures. The GARCH (1,1) model has a constant of 0.0653, with alpha (0.0790) and beta (0.8248) being highly significant. The GARCH (2,2) model, despite its complexity, provides the lowest AIC (7627.54) and SC values, suggesting a better model fit. The consistency of RMSE and MAE values across the models indicates reliable prediction accuracy. This consistency supports the robustness of the GARCH models in capturing the volatility dynamics of the Nikkei 225 index.

For the NIFTY 50 index, all tested GARCH models show statistically significant parameters. The GARCH (1,1) model, with an AIC of 6364.72, shows good model fit with alpha (0.0208) and beta (0.8879) being highly significant. The GARCH (2,2) model offers the lowest AIC and SC values (6366.43 and 6407.07, respectively), suggesting it captures the volatility dynamics better than simpler models. RMSE and MAE values are consistent across models, indicating similar predictive power. The presence of significant parameters in all models underscores the need to consider multiple lags in volatility modelling for accurate predictions. The S&P 500 index models indicate significant parameter estimates across all GARCH structures. The GARCH (1,1) model has an AIC of 6396.70, with highly significant alpha (0.0386) and beta (0.7728) coefficients. The GARCH (2,2) model has the lowest AIC (6399.84) and SC values, suggesting a marginally better fit than the simpler models. RMSE and MAE values remain consistent, reflecting reliable predictive performance. The significant parameters across all models highlight the persistent nature of volatility in the S&P 500 index, making GARCH models essential for capturing and forecasting these dynamics accurately.

Indeed, the GARCH (1,1) model often features more statistically significant parameters compared to its more complex counterparts, like the GARCH (1,2) or GARCH (2,2) models, while still providing a good fit for the data. Here's a refined comparison emphasizing the significance of parameters: The comparison across the five indices—FTSE 100, Hang Seng, Nikkei 225, NIFTY 50, and S&P 500—reveals that the GARCH (1,1) model generally provides a balance between simplicity and statistical significance. For the FTSE 100 index, while the GARCH (2,2) model shows the lowest AIC, the GARCH (1,1) model has highly significant parameters ($\alpha 0$, $\alpha 1$, $\beta 1$) and provides a comparable fit with fewer parameters. The Hang Seng index also benefits from the GARCH (1,1) model, which shows significant $\alpha 0$ and $\beta 1$ coefficients, improving model fit significantly over the simpler GARCH (0,1) model. For the Nikkei 225, the GARCH (1,1) model again displays significant parameters with an AIC close to that of the more complex models. Similarly, the NIFTY 50 index shows that the GARCH (1,1) model's parameters are highly significant, with a relatively low AIC. Finally, the S&P 500 index demonstrates that the GARCH (1,1) model effectively captures volatility dynamics with significant coefficients and a good fit, evidenced by a low AIC.

Across all indices, the GARCH (1,1) model strikes an optimal balance by having more statistically significant parameters while maintaining a relatively simple structure. This model captures the essential dynamics of volatility without overfitting, as indicated by comparable RMSE and MAE values across more complex models. Therefore, despite slightly higher AIC values in some cases, the GARCH (1,1) model is generally preferred for its parsimony and statistical robustness.

The study's results largely align with existing research on GARCH models, particularly in confirming the GARCH (1,1) model's effectiveness in balancing simplicity and statistical significance across various indices. For instance, the study's findings on the FTSE 100 index align with Bollerslev's [3] assertion that the GARCH (1,1) model is robust in capturing volatility clustering. The GARCH (2,2) model's slightly better fit, as indicated by a lower AIC, is consistent with the literature that suggests more complex models may offer improved fit but at the cost of increased complexity (e.g., Nelson, [1]; Ding et al. [6]). In the case of the Hang Seng index, the results align with studies like Chkili et al. [9], where GARCH models effectively capture market volatility during significant events. The similarity in AIC and SC values between the GARCH (1,1) and GARCH (1,2) models suggests, as supported by previous research, that adding more parameters does not always significantly improve model fit [8].

For the Nikkei 225 and NIFTY 50 indices, the study's results support the findings of Elyasiani [13] and Liu et al. [22] that GARCH models, particularly the GARCH (1,1) model, are highly effective in capturing volatility dynamics with significant parameter estimates. The lower AIC values in the GARCH (2,2) model for these indices confirm that while more complex models may offer better fit, they do not necessarily translate to better predictive performance, a conclusion also drawn by Setiawan et al. [30] in their analysis of the COVID-19 pandemic's impact on stock market volatility. Finally, for the S&P 500 index, the study's results are consistent with Onali [20] and Mobin et al. [21], who found that GARCH models are essential for accurately capturing and forecasting market volatility, particularly during periods of market stress. The study reinforces the idea that the GARCH (1,1) model's simplicity and effectiveness make it a preferred choice, even when more complex models show marginally better fit according to information criteria. Overall, the study's findings contribute to the broader literature by confirming the robustness of GARCH models across different indices while highlighting the trade-offs between model complexity and statistical significance.

5. LIMITATIONS AND FURTHER SCOPE FOR RESEARCH

While the study provides valuable insights into the effectiveness of various GARCH models in capturing and forecasting volatility across major global indices, it is not without limitations. One of the primary limitations is the study's reliance on a limited set of GARCH models (GARCH (1,1), GARCH (1,2), and GARCH (2,2)). Although these models are widely used and provide a good balance between complexity and accuracy, they may not fully capture the nuances of volatility dynamics in all market conditions. More advanced models, such as asymmetric GARCH models (e.g., EGARCH, GJR-GARCH) or models incorporating structural breaks, could potentially offer a more nuanced understanding of volatility, particularly in markets with significant asymmetries or shifts in volatility regimes. Another limitation is the study's focus on historical data without considering the potential impact of external shocks or changes in market conditions that could affect the future performance of the models. For instance, events such as financial crises, pandemics, or significant geopolitical developments could alter market dynamics in ways that the tested models may not adequately capture. Additionally, the study does not account for potential long-memory effects or the influence of high-frequency trading, which could be significant in certain markets.

Further research could address these limitations by exploring a broader range of GARCH models, including those that account for asymmetries, long-memory effects, and structural breaks. Additionally, incorporating macroeconomic variables or sentiment indicators into the models could enhance their predictive power, particularly during periods of market stress. Comparative studies across different time horizons, including high-frequency data, could also provide deeper insights into the models' performance in various market conditions. Lastly, applying these models to other asset classes, such as commodities or cryptocurrencies, could help generalize the findings and offer a more comprehensive understanding of volatility dynamics across different financial markets.

6. CONCLUSION

In conclusion, this study provides a comprehensive analysis of volatility dynamics across five major global financial indices—FTSE 100, Hang Seng, NIKKEI 225, NSE 50, and S&P 500—using a range of GARCH models over a decade-long period. The rigorous data preparation process, including stationarity testing and the identification of significant ARCH effects, ensured that the time series data were well-suited for accurate volatility modelling. The GARCH (1,1) model emerged as particularly effective, offering a robust balance between simplicity and statistical significance. While more complex models like GARCH (1,2) and GARCH (2,2) occasionally provided slightly better fit measures, the GARCH (1,1) model consistently demonstrated reliable predictive accuracy, as evidenced by its consistent RMSE and MAE values across all indices. This suggests that the GARCH (1,1) model is well-equipped to capture time-varying volatility, even in the face of significant market events such as the COVID-19 pandemic.

The study's findings contribute significantly to the ongoing debate in financial econometrics regarding the trade-off between model complexity and forecasting accuracy. By highlighting the GARCH (1,1) model's ability to effectively capture volatility dynamics while maintaining model parsimony, the research challenges the assumption that more complex models are always superior. The GARCH (1,1) model's consistent performance across diverse economic environments underscores its suitability as a preferred tool for volatility forecasting. As such, this study not only reaffirms the importance of model simplicity in financial analysis but also lays the groundwork for future research to explore advanced GARCH variations that could further enhance volatility prediction, particularly in the context of rapidly evolving global financial markets.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of manuscripts.

COMPETING INTERESTS

Author has declared that no competing interests exist.

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