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ORIGINAL PAPER

Exploring Japanese stock market volatility using symmetric and asymmetric GARCH models: A case study

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Abstract:
The main aim of this research paper is to investigate Japanese stock market volatility using symmetric and asymmetric GARCH models. The Nikkei 225 index is the Tokyo Stock Exchange index of 225 publicly owned liquid companies across industries, and the index is calculated using price-weighted-average method. It has been very effective in representing the market sentiment and macroeconomic condition of Japanese Stock market, in this context due to lack of related studies it becomes imperative to study the volatility of the Index. For this purpose, the following models, such as: GARCH, I-GARCH, T-GARCH, E-GARCH, P-GARCH, AP-GARCH (APARCH) were tested across Normal Distribution, Student's T Distribution, Generalized Error Distribution, Parametric T distribution and Parametric Generalized Error Distribution. Based on AIC, SIC and Log Likelihood APARCH at Generalized Error Distribution was chosen. The model displayed strong forecasting capability and from the analysis volatility clustering and asymmetry was evident. It was also identified that the index is sensitive to the leverage effect.

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JEL Classification: C22, C58, G1, G12, G15

Introduction

Volatility is one of the most important factors that is considered while reviewing any time series for any purpose. In the context of financial time series, volatility holds various connotations not only related to plain statistics, but every movement has deep impacts both intrinsically and extrinsically, and holds the attention of not only investors but also academicians and policymakers at large. In this context, stock exchange indices are the indicator of the overall market and are sensitive to even small changes in the macroeconomic context.

One of the major stock exchanges in the world is the Tokyo Stock Exchange (TSE) and which is among the top 5 stock exchanges based on market capitalization. Very little attention has been paid by the academic community to the Japanese stock market and its other possibilities (Kato & Schallheim, 1985). The clearing facilities at Tokyo stock exchange is noisy and inefficient (Amihud & Mendelson, 1991). A sentiment analysis done using positive and negative affirmations in the Wall Street Journal and the NIKKEI index helped in predicting prices 3 days in advance.(Ishijima et al., 2015). The Exchange operates in 2 sessions, 9:00 AM to 11:30 AM and 12:30 PM to 3:30 PM.

NIKKEI 225 is a price-weighted average index of 225 highly capitalised and liquid, publicly-owned companies across various industries, operating in Japanese Yen. An excellent and curious investigation has been made, where it has been noted that some stocks in the index is overweighed by a factor of 10 or more, and co-movement with stocks within the index has positive correlation and has a negative correlated co-movement with stocks outside the index. (Greenwood, 2008). NIKKEI 225 ETFs occupy almost 2% of NIKKEI 225 stocks, and due to macroeconomic trends, the deviations are observed (Hanaeda & Serita, 2017). This selected stock market index seems to be an effective indicator for the market sentiment and macroeconomic variables in Japanese stock market.

Literature review

Over time, a variety of empirical studies focused on the stock markets behavior have been consolidated in the specialized literature using GARCH family models, such as the following: Kumar et al. (2023a), Spulbar et al. (2023), Meher et al. (2024), Birau et al. (2021), Trivedi et al. (2021), Kumar et al. (2023b), Birau and Trivedi (2013) and many others.

Birau et al. (2014) have investigated the dynamics of the emerging stock market in India for the sample period from January 2002 to June 2014 based on GARCH (1,1) model. Moreover, Spulbar et al. (2022) have conducted an empirical research study in order to examine the behavior of the developed stock market in Japan, considering the daily prices of NIKKEI 225 stock index. The econometric framework was based on GARCH models, such as GARCH (1,1), EGARCH (1,1) and GJR (1,1) models and the sampled period was very long, from July 1998 to January 2022, but consisting of daily observations.

Nakayama and Yokouchi (2025) investigated the complex behavior of the developed stock market in Japan considering the impact of the news. Marumo and Li (2024) conducted an empirical study on the behavioral dynamics of stock markets in Japan and Australia under the influence of risk, based on ASX 200 and Nikkei 225 stock indices, using expectile regression model. Moreover, in the literature there is a wide variety of empirical studies that comparatively analyze the behavior of certain stock markets, such as: Trivedi and Birau (2013a), Birau et al. (2023), Trivedi and Birau (2013b), Siminica and Birau (2014).

In this context, not only the price movement but also the deviance from the mean value becomes important for a greater understanding of investment, economy, and policy-level purposes. Noting the volatility of an index or any financial time series is not exclusive to statistical areas but has wider implications holistically. Due to this very reason, anyone interested in Japan in terms of an economic point of view, NIKKEI 225 stock index should be their first source of enquiry. Understanding the volatility of this index thus becomes very imperative. There are several approaches to calculating the volatility and one of the most advanced and precise tools available in econometric terms is understanding Autoregressive Conditional Heteroskedasticity in Autoregressive (AR) and Moving Average (MA) terms. One of the latest models in that certain context is the GARCH family models, each model having the capability to calculate conditional volatility along with slight modifications based on distribution and Asymmetric configurations. One of the recent improvements in financial time series analysis is being used in terms of Machine Learning models using Neural Networks, however, its utility is more towards forecasting and not volatility analysis. In one of the studies 71 parameters were utilised and using 18 variables ANN architecture was effective in predicting the NIKKEI 225 prices (Qiu et al., 2016).

Research Methodology

The application of data is based on secondary data, and the data are quantitative in nature. This work analyses various methods to evaluate the quantitative impact of NIKKEI 225, the Tokyo Exchange stock. The volatility analysis is observed for 1334 days from 07/10/2019 to 21/03/2025. Log return had been calculated to make the data stationary. Volatility clustering had been spotted in data that leads to applying the ARCH LM test for heteroscedasticity in the return series residuals. Volatility has been proved by using different GARCH family models employing different distributions, such as the Normal (Gaussian), Student's t, and Generalised Error Distribution (GED), both with and without pre-specified parameters. The selection of the most suitable GARCH model for analysis is based on the values of AIC, SC, and Log Likelihood. The software package used for financial econometric analysis is EViews 12.

Significance of the study

The research delivers societal value through a more comprehensive insight into the dynamics of financial markets. GARCH models are applied to observe the volatility of the NIKKEI 225 index. A thorough understanding of market volatility is essential for investors, financial institutions, and government bodies, as it helps them to mitigate risks, improve their decisions and create better, more effective strategies. Existing literature is scarce on the subject, and no study so far has explored the individual analysis of NIKKEI 225. The study has high significance not only for the investors but also equally important for corporations to understand index dynamics, as they are influenced by both internal factors and external environmental conditions.

Limitations of the study

The study offers a detailed volatility analysis using daily data and focuses on conditional return variance, simplifying real-world complexities and creating a generalised framework that's more theoretical than practical, and it might not fully answer all relevant questions.

- Limited availability of data: Data was extracted from the Tokyo stock exchange database, which is freely available. Lack of financial backing meant this study had to take a general approach, unable to delve into the details of micro-level variations.
- Generalisation of result: Despite its flexibility and ability to cover several GARCH models, APARCH model struggles to capture the subjective nature in complex real-world scenarios.
- Model sensitivity to varied situations: APARCH model is great for understanding volatility on a theoretical level, accounting for various factors like leverage and decay effects, and volatility clustering**.** However, it might struggle to uncover the subtler, unique drivers of a particular situation.

Acknowledging the unique strengths and weaknesses of both the APARCH and GARCH models, we'll now move forward with the analysis and estimation in the research.

Empirical analysis, estimation, and results

For a better understanding of price movement, we look at the price movement visually. Below is the graphical representation of actual prices.

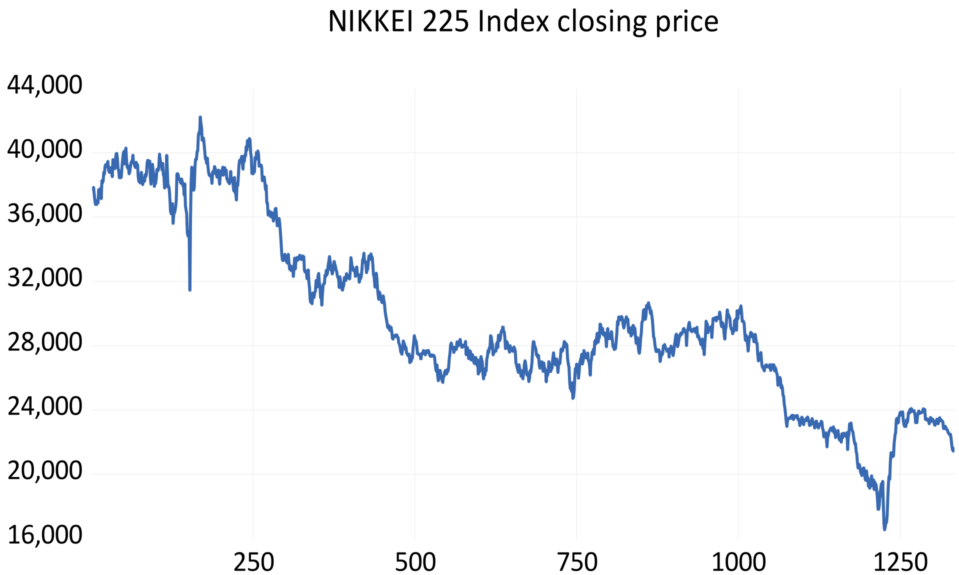


Figure 1. Daily Closing Price of Index
Source: author's Computation using EViews 12

The above graphical representation is of the NIKKEI 225 index price over a given time period, showing a clear overall downward trajectory. Index begins at a high level, above 36000 and rises briefly above 40000 and then drops sharply. The early phase of the graph reflects significant market volatility, with fluctuation indicating the period of instability. After the initial fall, the index continues to decline slowly, with small ups and downs, interspersed with minor recoveries. This phase suggests market stabilisation, but fails as the overall market movement remains downward. Around the midpoint of the graph, the index fluctuates between 26000 and 28000, which shows a sign of unification. In the later stages, the declines become steeper once again, and the index falls below 20000 before a slight recovery at the end. The pattern shows how the Japanese stock market dropped a lot after a big rise and took a long time to recover.
To make returns stationary, the log return has been calculated, and the below is the graphical representation of the log return. As discussed earlier that there are fluctuations over the period of time.

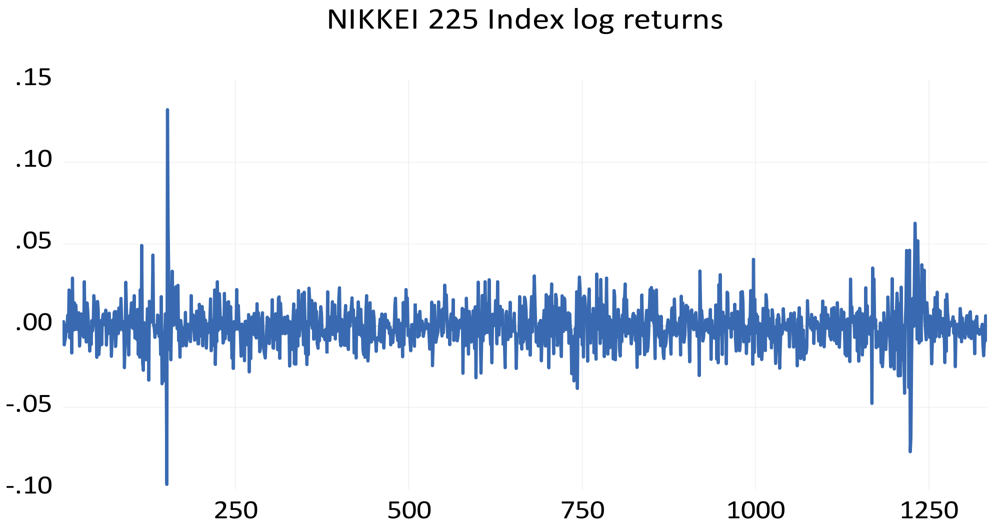


Figure 2: Log Returns Graph
Source: author's Computation using EViews 12

The visual pattern hints at possible heteroscedasticity. It is crucial to first verify the stationarity of the data.

Test of stationarity

Null Hypothesis: NIKKEI_225_INDEX_LOG_RETURNS has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC, maxlag=22)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-36.98114	0.0000
Test critical values:	1% level	-3.435049	
	5% level	-2.863502	
	10% level	-2.567864	

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

Table 1 Augmented Dickey-Fuller (ADF) test
Source: Author’s computation using EViews 12

The above test is an Augmented Dickey-Fuller test, and it can be observed that the probability value is less than 0.05. Consequently, we reject the Null hypothesis test, and the given data has no unit root and is stationary.

Descriptive Statistics

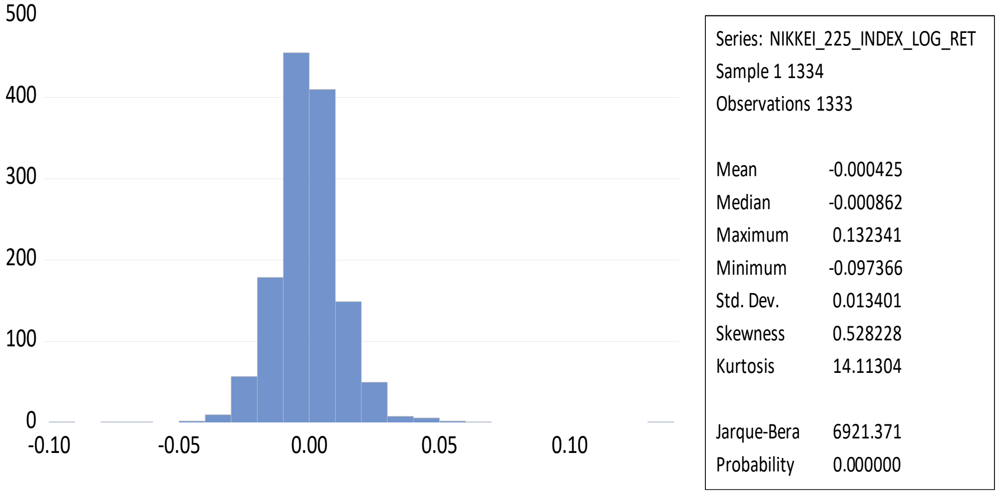


Figure 3: Test Distribution Analysis
Source: Author’s computation using EViews 12

The above statistics show that the average log return is scarcely negative. The central value is approximately close to zero, suggesting a nearly symmetric distribution. The standard deviation is very low, which signifies that most of the datasets are close to the mean value and less deviated.A high kurtosis value shows a leptokurtic distribution and slight positive skewness, which indicates extreme values as compared to a normal distribution. To analyse further, we need to check the ARCH effect on the given dataset through the ARCH LM Test.

Heteroscedasticity Test

Heteroskedasticity Test: ARCH			
F-statistic	474.9144	Prob. F(1,1329)	0.0000
Obs*R-squared	350.4108	Prob. Chi-Square(1)	0.0000

Table 2. ARCH effect test
Source: Author’s computation using EViews 12

From the above table, it can be observed that the ARCH test result shows the p-value (0.0000) is strong substantiation of the ARCH effect in the given dataset, suggesting that the data exhibits volatility clustering.

		GARCH	IGARCH	TARCH	EGARCH	PARCH	APARCH
Normal Distribution	*Akaike info criterion*	-5.987515	-5.94637	-6.01175	-5.99922	-5.98728	-6.01263
	Schwarz criterion	-5.968017	-5.934671	-5.98835	-5.97582	-5.96388	-5.98533
	Log Likelihood	3992.685	3963.283	4009.826	4001.48100	3993.52600	4011.409
	ARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	significant coefficient	Yes	Yes	Yes	Yes	Yes	Yes
Student's T	*Akaike info criterion*	-6.022177	-5.95762	-6.03515	-6.02919	-6.02067	-6.03387
	Schwarz criterion	-5.998779	-5.94794	-6.00785	-6.00189	-5.99337	-6.00268
	Log Likelihood	4016.77	3967.835	4026.41	4022.44	4016.764	4026.56000
	ARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	significant coefficient	Yes	Yes	Yes	Yes	Yes	Yes
Generalized Error	*Akaike info criterion*	-6.024738	-5.97943	-6.03931	-6.03251	-6.02335	-6.038316
	Schwarz criterion	-6.001339	-5.96137	-6.01201	-6.00521	-5.99605	-6.007118
	Log Likelihood	4018.475	3987.32	4029.179	4024.653	4018.548	4029.519
	ARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	significant coefficient	Yes	Yes	Yes	Yes	Yes	Yes
T distribution (Parameter)	*Akaike info criterion*	-6.022152	-5.988011	-6.03610	-6.02915	-6.02070	-6.03496
	Schwarz criterion	-6.002654	-5.97631	-6.01270	-6.00575	-5.99730	-6.00766
	Log likelihood	4015.754	3991.015	4026.044	4021.413	4015.788	4026.28300
	ARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	significant coefficient	Yes	Yes	Yes	Yes	Yes	Yes
Generalised Error	*Akaike info criterion*	-6.024042	-5.992784	-6.04004	-6.03236	-6.03922	-6.03922
	Schwarz criterion	-6.004543	-5.981084	-6.01664	-6.00896	-6.01192	-6.01192

(Parameter)	***Log Likelihood***	4017.012	3994.194	4028.667	4023.554	4029.117	4029.117
	ARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	Autocorrelation	No	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No	No
	GARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
	significant coefficient	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: Decision Table
Source: Author's tabulation using MS Office

Implementing GARCH, IGARCH, TARCH, EGARCH, APARCH, and PARCH among Gaussian Normal Distribution, Student's t distribution, Generalised Error distribution(GED), t distribution, and GED with fixed parameter, from the above table, it can be concluded that APARCH model generalised error distribution is the most suitable model due lowest Akaike info criterion (-6.038316), the lowest Schwarz criterion (-6.007118) and the highest Log likelihood (4029.519).

Dependent Variable: NIKKEI_225_INDEX_LOG_RETURNS
Method: ML ARCH - Generalised error distribution (GED) (Marquardt / EViews legacy)
Date: 05/22/25 Time: 23:01
Sample (adjusted): 2 1333
Included observations: 1332 after adjustments
Convergence achieved after 26 iterations
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(7) = C(3) + C(4)*(ABS(RESID(-1)) - C(5)*RESID(-1))^C(7) + C(6)*@SQRT(GARCH(-1))^C(7)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.001017	0.000297	-3.427512	0.0006
NIKKEI_225_INDEX_LOG_RETURNS(-1)	-0.018951	0.027380	-0.692147	0.4888
Variance Equation				
C(3)	1.18E-06	3.27E-06	0.361834	0.7175
C(4)	0.054931	0.046643	1.177695	0.2389
C(5)	0.620136	0.451933	1.372185	0.1700
C(6)	0.813824	0.047169	17.25336	0.0000
C(7)	2.530963	0.648632	3.902002	0.0001
GED PARAMETER	1.426157	0.073738	19.34081	0.0000

R-squared	-0.001710	Mean dependent var	-0.000427
Adjusted R-squared	-0.002463	S.D. dependent var	0.013406
S.E. of regression	0.013422	Akaike info criterion	-6.038316
Sum squared resid	0.239608	Schwarz criterion	-6.007118

Log likelihood	4029.519	Hannan-Quinn criter.	-6.026625
Durbin-Watson stat	1.984487		

Table 4 APARCH(1,1) generalised error distribution
Source: Author's computation using EViews 12

From the above APARCH(1,1) model, it can be concluded that C6 has strong volatility clustering, which also states that past volatility influences future volatility. C4 and C5 are not statistically significant, the overall model effectively captures the volatility clustering. The GED Parameter is also highly significant. Durbin-Waston stat (1.984487), which indicates there is no major autocorrelation in residuals. Model diagnostics also include Akaike info criterion(-6.038316), Schwarz criterion (-6.007118) and Log likelihood(4029.519), suggesting a well-fitting model.There is a chance of volatility clustering and the leverage effect. The result also emphasises market risks, which is important for investors and risk managers.

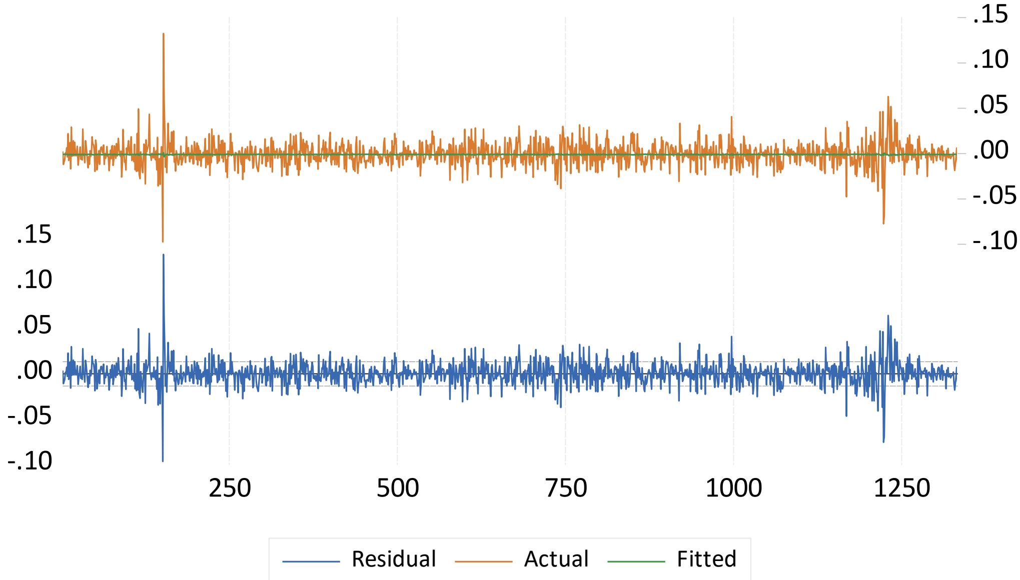
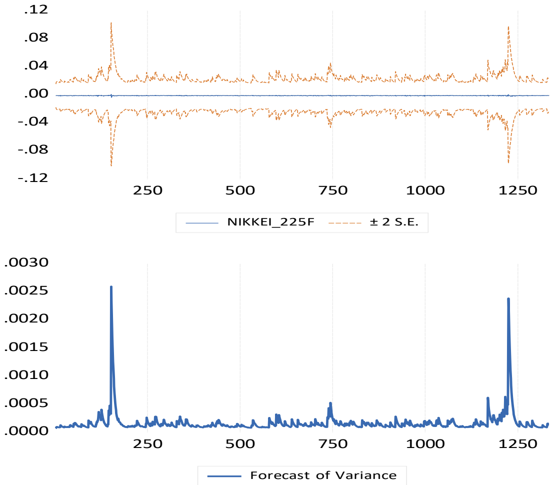


Figure 4. Graphical representation of estimated volatility
Source: author's Computation using EViews 12



Forecast: NIKKEI_225F	
Actual: NIKKEI_225_INDEX_LOG_RETURNS	
Forecast sample: 1 1334	
Adjusted sample: 2 1334	
Included observations: 1333	
Root Mean Squared Error	0.013412
Mean Absolute Error	0.009425
Mean Abs. Percent Error	NA
Theil Inequality Coef.	0.928309
Bias Proportion	0.001883
Variance Proportion	0.960821
Covariance Proportion	0.037297
Theil U2 Coefficient	NA
Symmetric MAPE	165.1441

Figure 5: Graphical representation of Forecast of Prices, Returns, and Volatility
Source: author's Computation using EViews 12

From the above pictures, it can be stated that the residuals are centred around zero, indicating there is no significant bias, and fitted values closely track actual returns. The difference between the actual value and the predicted value is small, and errors are close to zero. Spikes in the forecast variance graph match the period of high market movement, which means the model successfully captures uncertainty and or increased risk. The model demonstrates strong forecasting capacity and appropriate for analysing and predicting market volatility of returns.

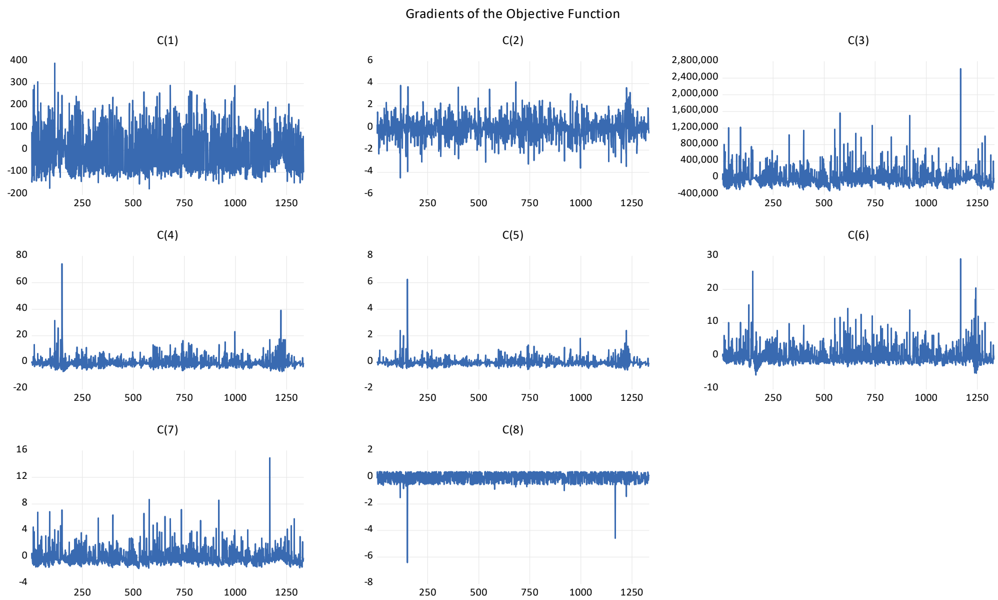


Figure 6: Gradients of the objective function
Source: author's Computation using EViews 12

The above graph shows the gradients of the objective functions from the coefficients C1-C8 in the model. Gradients help to assess how sensitive the objective functions. The gradients are fairly stable and fluctuate around zero, indicating that the model parameters were estimated efficiently and the optimization process was smooth. Parameters C3 and C6 show occasional spikes, which indicate that there are temporary effects due to market volatility. C3 is associated with the variance constant, which shows higher volatility. C8 remains close to zero, implying it was estimated with greater precision and had less impact on instability.

Conclusions and recommendations

A study comparing GARCH, TGARCH, IGARCH, EGARCH, PARCH, and APARCH models across six different distributions founds that the APARCH model with generalised error is the fittest model for the analysis of NIKKEI 225 index, and it was concluded that there was asymmetric, volatile clustering, leverage effect and volatility. Although APARCH model is a fine model, it fails to incorporate other finer details caused by the other variables, resulting in the generalisation of calculated results. For the academic community, it is essential to do an in-depth analysis of other finer details to avoid the generalisation of results. For this, various models are used, such as ML, AI, VAR, COPULA, etc., which are multivariate and show the larger picture that benefits society, investors and government for better policy formulation.

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