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MODELLING STOCK RETURNS VOLATILITY ON TOKYO STOCK EXCHANGE LIMITED

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ABSTRACT

This study empirically investigates the volatility pattern of the Tokyo stock exchange based on time series data which consists of monthly closing prices of the Nekkei Index for the seventeen years from 2000 to 2017. The present study has employed various autoregressive conditional heteroscedasticity (ARCH) family models such as generalized autoregressive conditional heteroscedasticity (GARCH), exponential GARCH (EGARCH), and threshold ARCH (TARCH) to appraise assorted nature of volatility patterns in the Tokyo stock market. Our findings suggest that the stock index fluctuated over the period. The negative skewness exhibits that return is negatively skewed. The negative skewness provides that the returns distributions of the market have a higher probability of providing a negative return. Jarque-Bera test examines the normality of return. It outlines that return is not normally distributed in the Tokyo stock exchange. Based on the unit root test, it has been observed that the index variable is stationary at the level. Moreover, the ARCH effect, GARCH effect, EGARCH, and PARCH effect are based on volatility models.

Keywords: Stock Exchange, Volatility, GARCH Models.

INTRODUCTION

Many empirical stock market return studies have indicated in favor of a non-constant variance (Fama 1965; Hathaway 1986). Stock return data have been considered by volatility clustering, where large returns follow large returns and small returns tend to be followed by small returns, leading to adjacent periods of volatility and steadiness (Apergis and Eleptheriou, 2001). Volatility is characterized as an indicator of the dispersion of returns for a given security and

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has long been considered a risk indicator. The higher the volatility, the riskier the security. Volatility has also been used as a central principle in modern financial theory (Bu et al., 2019). Several eminent scholars introduced a different types of volatility models. Engle (1982) build a model for the analysis of time-varying variance. This methodology – the Autoregressive Conditional Heteroskedastic (ARCH) approach – introduce a return model that allows for a shift in conditional variance. The basic ARCH model has led to other similar formulations explaining the evolution of time series variance. The most commonly used of these other formulations has been the Generalized ARCH (GARCH) model. Stochastic volatility proposed by Heston (1993), realized volatility calculated from high-frequency data proposed by Andersen and Bollerslev (1998), and forecasting future volatility proposed by Andersen et al. (2001).

LITERATURE REVIEW

Several research was made on modeling the stock return volatility both in advanced and growing countries. Fong (1997) investigated regime shifts and volatility patience in the Japanese inventory marketplace. He determined that the Switching ARCH (SWARCH) model provides a higher description of the data and implies a much decrease degree of volatility patience than conventional ARCH fashions. He only considered the ARCH model and ignored other models like PARCH, E-GARCH, TARCH models.

Liu and Lee (2001) investigated the effectiveness of momentum techniques in the Japanese inventory market at some point in the period of 1975 to 1997. The essential findings of this research are that momentum method portfolio, which puts money into past three-to-twelve month's winners and promotes beyond 3-to-twelve month's losers lose approximately 0.5 percent consistent with month's over the following 3 to one year. This means that stock prices in the Japanese stock market overturn rather than persist over a medium-term sphere. For analyzing data, they introduce mean, standard deviation, and t-test and ignore other models like ARCH, PARCH, E-GARCH, TARCH models.

Reyes (2001) examined volatility transfers between size-based stock indexes from the Tokyo Stock Exchange. He used a bivariate EGARCH model to check for volatility spillover results among large- and small-cap inventory indexes. He discovered an uneven volatility spillover from massive-cap stock return to small-cap return, but no longer vice versa. He introduces the E-GARCH model and ignores other models like ARCH, PARCH, TARCH models for analyzing data.

Takemori and Wada (2003) investigated the contrasting performance of Korean and Japanese stock markets before and after the East Asian forex disaster. The Korean stock markets confirmed a sharper decline and a faster recuperation than the Japanese inventory market. They empirically prove that the theoretical version in this paper has some quantitative aid by means of thinking about the extent of monthly inventory market capitalization and the return on the everyday stock index in Korea and Japan. For analyzing data, they introduce mean, and they fail to introduce a sophisticated volatility model.

Kubota and Takehara (2004) investigated whether or not the interest of economic corporations creates fee and/or danger to the economy in the asset pricing framework. They used inventory return information from nonfinancial corporations listed in the first phase of the Tokyo Stock Exchange. They argued that the augmented index model performs properly each with cross-sectional Fama and MacBeth regression take a look at and GMM test. They mainly focused on the CAPM model and GMM model and ignored other models like ARCH, PARCH, E-GARCH, TARCH model.

Liu and Zhu (2009) investigated the volatility influences of the total commission deregulation in Japan. They also discovered that deregulation typically tends to significantly increase rate volatility in the Japanese equity marketplace. They advised that imposing a higher transaction price would possibly nevertheless be a feasible coverage device for stabilizing the market with the aid of curbing quick-time period noise trading. For analyzing data, they introduce mean, standard deviation, and dummy variable regression models and ignore other models like ARCH, PARCH, E-GARCH, TARCH models.

Walid (2009) tested whether or not the go-sectional versions in stock return are best described by way of systematic danger factors or with the aid of company characteristics consisting of e-book-to-marketplace ratios and market capitalization. He recommended that both the firm length and book-to-market ratio are drastically related to average return charges. He mainly focused on the FAMA model and GMM model and ignored other models like ARCH, PARCH, E-GARCH, and TARCH models.

Kubota and Takehara (2017) investigated the time-series properties of accounting earnings and their components. They propose a new measure of earnings persistency in accordance with the vector autoregressive (VAR) model–linked earnings and stock returns. They estimate the first-order autocorrelations and test the stationarity of five variables: earnings, cash flows from operations, total accruals, current accruals, and noncurrent accruals. They mainly focused on the VAR model and ignored other models like ARCH, PARCH, E-GARCH, TARCH models.

Yıldırım and Ünal (2017) proposed a new outlook to model the Tokyo stock exchange market's volatility (Nikkei225) in the concept of continuous-time GARCH (1,1) model. The data covers the period from 2005 to 2013. The study's empirical results show that continuous-time GARCH (1,1) driven by a Meixner Lévy process successfully captures the volatility clustering and heavy-tail behavior of Nikkei225. They mainly focused on GARCH and CO-GARCH models and ignored other models like ARCH, PARCH, E-GARCH, TARCH models.

Cevik et al. (2020) examined the relationship between crude oil prices and stock market returns in Turkey. They mainly use weekly data from 1990 to 2017. For checking stationary, they mainly use ADF, PP, KPSS tests. For checking volatility, they use the E-GARCH model. The results of the study show that changes in global oil prices significantly affect stock market returns in Turkey. They ignore other models like ARCH, PARCH, and TARCH models.

Fousekis (2020) investigated the relationship between stock returns and changes in risk perceptions. For checking stationary, he introduced the KPSS test. For analyzing time-series data, he introduced Kendall's tau statistics and non-parametric local regression model. The results of the study show that the association between the two variables is negative. He ignored other models like ARCH, PARCH, E-GARCH, TARCH models.

From the above investigation, no research has been conducted on the Tokyo Stock Exchange using ARCH, PARCH, E-GARCH, TARCH model, and it adds new literature on the stock exchange field.

OBJECTIVES OF THE STUDY

The study's primary objective is to fit the appropriate GARCH model to estimate market volatility based on the Nekkei index. The paper aims at:

- To investigate the volatility pattern of the Nekkei index using symmetric and asymmetric models.

HYPOTHESIS

ARCH -GARCH Model

H_0: There is no ARCH (Auto-Regressive Conditional Heteroscedasticity)
H_1: There is an ARCH effect

METHODOLOGY

Data

The study is based on the secondary data that was collected from the website of the Tokyo Stock Exchange. Monthly closing prices of all share index data over a period of 17 years extending from 2000 to 2017 were used.

Asset Returns

$r_t = \log(p_t/p_{t-1})$ x100
r_t= is the logarithmic yearly return
p_t and p_{t-1} denote the closing market index at the current (t) and previous year (t - 1).

Models

Autoregressive Conditionally Heteroscedastic (ARCH) Models

One particular non-linear model in widespread usage in finance is known as an 'ARCH' model (ARCH stands for 'autoregressive conditionally heteroscedastic'). Another important feature of many series of financial asset returns that provides a motivation for the ARCH class of models is known as 'volatility clustering' or 'volatility pooling.' Volatility clustering describes the tendency of large changes in asset prices (of either sign) to follow large changes and small changes (of either sign) to follow small changes. In other words, the current level of volatility tends to be positively correlated with its level during the immediately preceding periods.

Generalized ARCH (GARCH) Models

The GARCH model was developed independently by Bollerslev (1986) and Taylor (1986). The GARCH model allows the conditional variance to be dependent upon its own previous lags. A GARCH model has two components: a mean equation and a variance equation. The mean equation is the OLS regression with an Autoregressive term, and the variance equation includes a constant, ARCH, and GARCH terms with account for volatility. Both mean and variance equations are jointly estimated using the Bollerslev-Wooldridge (1992) Quasi-maximum likelihood technique. The GARCH model is symmetric and does not capture the asymmetry effect (leverage effect). Threshold GARCH or TGARCH proposed by Zakoian (1994) and the Exponential GARCH or EGARCH proposed by Nelson (1991) models are more appropriate to absorb the possible asymmetry effect of the stock market behavior (Gbeda and Peprah, 2018).

The EGARCH model

The exponential GARCH model was proposed by Nelson (1991). There is no need to artificially impose non-negativity constraints on the model parameters. Second, asymmetries are allowed for under the EGARCH formulation, since if the relationship between volatility and returns is negative, γ, will be negative. Note that Nelson assumed a generalized error distribution (GED) structure for the errors in the original formulation. GED is a very broad family of distributions that can be used for many types of series. However, owing to its computational ease and intuitive interpretation, almost all applications of EGARCH employ conditionally normal errors rather than using GED (Brooks, 2014).

The TGARCH model

TGARCH is an extension of the GARCH model with an additional term that accounts for asymmetries (asymmetry effect). The asymmetry effect refers to the tendency that bad news tends to increase stock returns volatility more than good news (Gbeda and Peprah, 2018).

PARCH Model

Ding, Granger, and Engle (1993) introduced a new class of ARCH models called the Power ARCH (PARCH) model. The model estimates the optimal power term. Thus, this model permits a virtually infinite range of transformations inclusive of any positive value.

RESULTS/ DISCUSSION

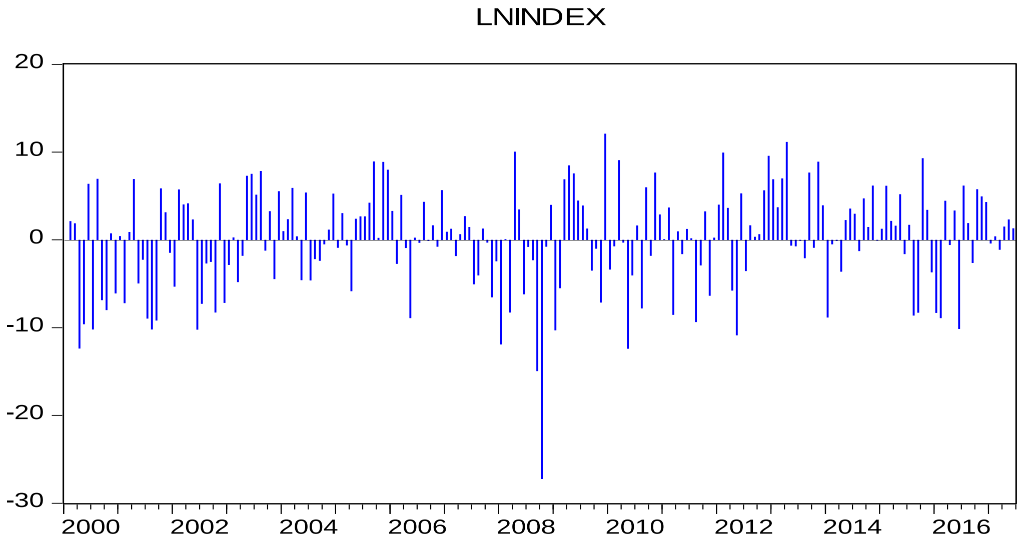

Figure 1 shows the fluctuating trend from 2000 to 2017 due to low and high volatility.

Table I: *Descriptive Statistics*

	LNINDEX
Mean	0.008965
Median	0.406968
Maximum	12.08881
Minimum	-27.21623
Std. Dev.	5.743019
Skewness	-0.753952
Kurtosis	4.505239
Jarque-Bera	39.53166
Probability	0.000000
Sum	1.873666
Sum Sq. Dev.	6860.313
Observations	209

The negative skewness provides that the returns distributions of the market have a higher probability of providing a negative return. The high value of kurtosis as compared to 3 exhibits that index return has a heavier tail than the standard normal distribution. Jarque-Bera test, which examines the normality of return, is significant at a 1 percent level of significance. It outlines that return is not normally distributed in the Tokyo stock exchange.

Table II: *Results of Unit Root Tests*

Variable	ADF	PP	KPSS	Order of Integration
LNINDEX	-12.41473*	-12.41473*	0.277702	I(0)

Note: * indicates significance at 1 percent level

The stationary properties of data have been confirmed by testing the standard procedure of unit root tests. We use the augmented Dickey-Fuller (ADF) test, Phillips–Perron (PP), and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. While the ADF and PP tests consider the null hypothesis that the variable has a unit root, the KPSS test considers the null hypothesis that the variable under consideration is stationary. The results of unit root tests have been presented in *Table II*. It can be observed from this table that the variable is stationary at level.

Table III: ARCH, TARCH, GARCH, EGARCH, and PARCH volatility coefficients for return series

Model *ARCH*	Co-efficient	Standard Error
Constant	0.001605	0.395819
LNINDEX(-1)	0.144250**	0.068930
GARCH/TARCH		
Constant	0.322905	0.398620
LNINDEX(-1)	0.139369	0.080676
GARCH(-1)	0.775978*	0.112863
EGARCH		
Constant	0.129662	0.384380
LNINDEX(-1)	0.170889**	0.069157
PARCH		
Constant	0.146153	0.392036
LNINDEX(-1)	0.164252**	0.078990

*and **denote significance at 1% and 5% levels, respectively.

Table III shows that there is an ARCH effect because it is significant at 5% level and there is GARCH effect, and it is significant at 1% level, and there is also EGARCH and PARCH effect and both cases it is significant at 5% level.

CONCLUDING REMARKS

In this study, the volatility of the Nikkei index return is tested using the symmetric and asymmetric GARCH models. The monthly closing prices of the Nikkei index for seventeen years are collected and modeled using different GARCH models that capture the volatility clustering for the study period, i.e., from 2000 to 2017. The results of the study show that the stock index fluctuated over the period. The negative skewness exhibits that return is negatively skewed. In addition, the negative skewness provides that the returns distributions of the market have a higher probability of providing a negative return. Jarque-Bera test examines the normality of return. It outlines that return is not normally distributed in the Tokyo stock exchange. Based on the unit root test, it has been observed that the index variable is stationary at the level. GARCH (1,1), EGARCH (1,1), and TGARCH (1,1) models are employed in the study. The results show that the coefficient sign both in the EGARCH (positive and significant) and PARCH (positive and significant) models. The study also examines the asymmetric nature of volatility. *Table III* provides that GARCH (1, 1) model is the best fit for forecasting the conditional volatility in the Tokyo Stock Exchange.

The findings suggest that volatility depends significantly on the past error term, representing an unexpected increase or decrease in return and volatility in the preceding period. In other words, the unforeseen rise or decline in stock returns and volatility in the last period together have impacted investors' behavior and thus their investment decisions. The study also reports the asymmetric effects of good and bad news on stock market volatility.

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