

Do the Selection of Volatility Models Depend on the Choice of Error Distributions: A Study on DS30 Index of the Dhaka Stock Exchange Limited, Bangladesh

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Abstract

Research purpose: This study aims to explore whether the choice of the error distributions matters in the case of selecting the best-fitted models for the 30 blue-chip stocks from the Dhaka Stock Exchange (DSE), Bangladesh.

Design/methodology/approach: The study encompasses the DS30 index of the DSE, from 1 January 2015 to 31 March 2025, and the data have been converted into logarithmic return form. To fulfill the objectives, the researchers compared the Generalized Autoregressive Conditional Heteroscedastic (GARCH) along with the Exponential GARCH (EGARCH) under three alternative error distributions, namely normal, Student's t, and generalized error distributions. Then, the researchers employed ARMA with GARCH and EGARCH techniques. For the model selections, two popular criteria — AIC and BIC — have been considered.

Findings: The models MA(1)-GARCH(1,2), MA(1)-EGARCH(1,1); MA(1)-GARCH(1,1), MA(1)-EGARCH(1,1); and MA(1)-GARCH(1,1), MA(1)-EGARCH(1,1) have been determined as the preferred models under Normal, Student's t, and Generalized error distributions, respectively. However, the models selected under Student's t error distributions have been proven to be superior. Hence, the choice of error distributions is crucial when modeling the volatility of the DS30 index.

Practical implications and originality: This is a novel research work that might guide the investors, who generally target the blue-chip stocks having good fundamentals, for their investments in DSE, Bangladesh.

Research limitations: The comprehensive nature of this investigation necessarily imposed certain methodological constraints, precluding the inclusion of several additional ARCH/GARCH variants and alternative distributional assumptions within the analytical framework.

Keywords: Stationary, Heteroscedasticity, Autocorrelation, GARCH, EGARCH, AIC, BIC

JEL classification: C520, C530

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1. Introduction

One notable aspect of the capital market is its volatility. It refers to the oscillations or spikes and drops of stock prices. Greater volatility increases investors' risks while simultaneously creating the potential for larger gains. Apart from investors' conservative stances, high market volatility shatters stock prices and breeds uncertainty, which reduces their accuracy as gauges of the company's inherent worth (Akhtar & Khan, 2016). Thus, during the past few decades, scholars, decision-makers, and practitioners have paid more and more attention to this aspect of the markets. To predict market volatility, researchers are constantly looking for more precise models. Forecasting volatility can also have a big impact on financial decisions, including choosing a portfolio, pricing options, managing risk, and setting monetary policy. Therefore, accurate modeling and forecasting of financial market volatility has remained a significant concern over time.

The DS30 index represents the performance of the 30 leading and highly liquid companies listed on this exchange. The DS30 index is treated as investable index which reflects around 51% of the total equity market capitalization of this exchange (Source: Dhaka Stock Exchange Ltd., www.dsebd.org). The companies within this index are blue-chips with having good fundamentals. Hence, a significant portion of the investors target the companies remain within this DS30 index for making their investments. Keeping the mind of that the market is not efficient and having comparatively high volatility, the investors who target the companies under DS30 always seek for the improved models for this index. Therefore, it is crucial for end users and other stakeholders to determine the best volatility model for this index. Nevertheless, the researchers' thorough search resulted in relatively few studies on this index. Despite the fact that Ali, 2018; Huq & Ali, 2018 investigated this index, they and a few others mostly utilized the most basic GARCH family order combinations (1,1) and even with a single error distribution. This study seeks to address this research gap by testing the order combinations of the models under three alternative error distributions: Normal Gaussian error distributions, Student's t error distributions, and Generalized error distributions. In doing so, the researchers want to uncover the answers to their query of whether the selection of volatility models is influenced by the choice of error distributions. GARCH (p,q) and EGARCH (p,q), two of the few GARCH family models, are also intended to be included under each of the three error distributions. These efforts will undoubtedly distinguish the study and assist the different stakeholders in making their own decisions.

2. Literature Review

The autoregressive conditional heteroscedasticity (ARCH) model developed by Engle (1982) was a significant breakthrough in time series modelling. However, one of the major limitations of this model was that it required a large number of parameters to predict the volatility. A few years later, another model named the generalized autoregressive conditional heteroscedasticity (GARCH) model was developed by Bollerslev (1986) as an alternative, where the conditional variance is allowed to depend upon its own lag, typically reducing the required number of ARCH lags in volatility prediction (Abdullah et al., 2017).

Furthermore, the conventional GARCH model contains certain limitations, such as it imposes a symmetrical volatility reaction to positive and negative shocks. This occurs because the conditional variance in its equations is determined by the magnitudes of the lagged residuals rather than their signs (Brooks, 2008). Several extensions, such as EGARCH, TGARCH, PARCH, and GARCH-in-mean, were developed to address the issues with standard GARCH (p,q) models.

Worldwide, a variety of volatility models are employed to parameterize and forecast stock market volatility based on various market features. Researchers have also attempted to use a variety of models over time to parameterize and estimate the volatility of Bangladesh's two stock exchanges, the Dhaka Stock Exchange Ltd. (DSE) and the Chittagong Stock Exchange Ltd. (CSE). Ahmed and Naher (2021) used ARMA(1,1) together with five different models (GARCH(1,1), EGARCH(1,1), TGARCH(1,1), APARCH(1,1), and IGARCH(1,1)) to predict the volatility of the daily closing prices of the Dhaka Stock Exchange Ltd., considering both normal and student's t error distributions. A study by Huq, Karim, & Ali (2017) demonstrated that an asymmetric TGARCH model was optimal for predicting volatility in both DSE and CSE markets in Bangladesh. Similarly, among ARMA(1,1) with GARCH, EGARCH, GJR-GARCH, and APARCH models, M. M. Huq & Ali (2018) found the GJR-GARCH model to be best for DSEX. In a separate study, Huq & Ali (2018) also compared different GARCH family models using two error distributions and determined that TGARCH(1,1) with Generalized error distributions was the most effective in forecasting the DS30 index. In contrast, Roni et al. (2017) discovered that the symmetric GARCH was superior in forecasting performance for DSE. The "leverage effect" was also noted by Karim et al. (2022) on the Bombay Stock Exchange (BSE) and the Dhaka Stock Exchange Ltd. (DSE). Singhanian & Prakash (2014) determined that GARCH(1,1) was most appropriate for Bangladesh, Sri Lanka, and India's Bombay Stock Exchange, while TGARCH(1,1) was found to be the best fit for India's National Stock Exchange, Pakistan, and the global market represented by S&P Global 1200. Meanwhile, Huq et al. (2013) determined the ARMA(1,1) with GARCH(1,1) and GARCH(2,1) models to be superior.

Some related studies related to the capital markets outside Bangladesh also extensively helped the present study. Arashi and Rounaghi (2022) modelled the daily stock index in the NASDAQ stock exchange and found that the ARMA-GARCH model can forecast very well at the error level of 1%. While for the Chinese stock market, Wang et al. (2022) found the ARMA (4,4)-GARCH (1,1) model, and ARMA(1,1)-TGARCH(1,1) to be superior for forecasting the Shanghai Composite Index and Shenzhen Component Index, respectively. Owji (2018) tried to parameterize the indices of three large European equity markets of the UK, Germany, and France and found GARCH (1,1) and EGARCH(1,1) to be the best performers. Devi (2018) also observed that the asymmetric EGARCH model outperforms the other asymmetric TGARCH and the symmetric GARCH in the USA and UK stock markets. Thalassinou et al. (2014) also found the asymmetric EGARCH model to be the best in a similar study in the case of the Czech stock market. However, Lim et al. (2023) found that the EGARCH model outperformed the stock exchanges of Thailand (SET), Bursa Malaysia Kuala Lumpur Composite Index (KLCI), Indonesia Stock Exchange Index (LQ45), and

Financial Times Stock Exchange (FTSE) when the "leverage effect" was present. In the case of the BSE 100 S&P stock index series, it was also discovered that the asymmetric EGARCH outperformed the GARCH and GJR-GARCH in out-of-sample volatility forecasting under the student's t distribution (Singh et al., 2023). Sharma and Vipul (2015) compared various GARCH family models using a sample of 21 major stock indexes from around the world, and found symmetric GARCH to have the most accurate one-step-ahead predictions for the daily conditional variances.

Therefore, variations in the findings of empirical investigations across the globe were noted. In modelling and predicting their volatility, some research indicated that asymmetric models were more appropriate, while other studies suggested that symmetric GARCH models were the most suitable. Hence, this study adopted both symmetric GARCH and asymmetric GARCH in parameterizing the DS30 index of the Dhaka Stock Index.

3. Research Design

The study's framework consists of a single phase that includes first collecting quantitative data, then observing stylized facts, conducting several preliminary tests, and comparing the results of estimating numerous order combinations to determine which one fits the data the best under various error distributions. The idea that no single combination under any single selected error distribution may fail to produce the best possible combinations is the basis of the technique's justification, which is inconsistent with the goals of the study. The researchers are interested in building the ARMA(p,q) to develop the mean equation after verifying the presence of ARCH effects are in the data. The researchers then want to employ symmetric GARCH(p, q) and asymmetric EGARCH(p,q) models independently under normal, student's t , and generalized error distributions to identify the best-fitted model combinations.

4. Material and Methods

4.1 Data and Its Transformation

Working directly with the price series is not recommended for numerous statistical reasons; instead, the raw price series should be converted into a series of returns (Brooks, 2008). An additional advantage of returns is that they are usually unit-free. The analysis encompasses the index of Blue-Chip stocks, i.e. DS30 index of the Dhaka Stock Exchange Limited, Bangladesh from 1st January 2015 to 31st March 2025, and the data was collected from DSE library. The daily closing prices of stock indices were transformed into returns using the following formula (Brooks, 2008; Rahman & Haq, 2022).

$$r_t = \ln \left(\frac{V_t}{V_{t-1}} \right) \dots\dots\dots (i)$$

Where, r_t the continuously compounded return at time t , V_t signifies the asset price at time t , V_{t-1} signifies the corresponding previous period's asset price and $\ln$ denotes the natural logarithm.

The symmetric GARCH along with an asymmetric GARCH named EGARCH model have been employed in this study. These models are as follows.

4.2 Generalized Autoregressive Conditional Heteroscedastic (GARCH) Models

Bollerslev (1986) introduced a significant extension of the ARCH model, known as the GARCH model, which provides a more detailed description of the volatility clustering phenomenon in financial time series. In this approach, the estimation of time-varying volatility is achieved by considering conditional variance as a GARCH process (Wang et al., 2022). A GARCH (p,q) model is defined as follows, assuming a log return series $r_t = \mu + \varepsilon_t$ where ε_t represents the error term at time t (Kosapattarapim, 2013). The ε_t adheres to a GARCH(p,q) model if

$$\varepsilon_t = \eta_t \sqrt{h_t} \quad \dots\dots\dots(ii)$$

$$h_t = \omega + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j h_{t-j} \quad \dots\dots\dots(iii)$$

where $\{\eta_t\}$ are i.i.d random variables with zero mean and unit variance; and ω, α_i and β_j are non-negative constants with $\sum_{i=1}^p \alpha_i + \sum_{j=1}^q \beta_j < 1$ to confirm conditional variance to be positive as well as stationary. When q equals zero, the procedure simplifies to the ARCH model.

The GARCH model offers the benefit of including and interpreting heteroscedasticity within the model (Wang et al., 2022). However, a drawback of the traditional GARCH model is its inability to elucidate the impact of leverage effects on financial returns (Kosapattarapim, 2013). Conventional GARCH models impose a symmetrical volatility reaction to positive and adverse shocks. This happens as the conditional variance in its equations is defined by the magnitudes of the lagged residuals rather than their signs. In other words, the sign is lost when the lagged error is squared. As a result, symmetric GARCH models often include different non-normal distributions to enhance the accuracy of volatility predictions. Introducing these enhancements to symmetric GARCH models resulted in the creation of asymmetric GARCH models. Various extensions to the GARCH model have been proposed due to observed issues with standard GARCH(p,q) models. These issues include violations of the non-negativity conditions in the estimated model and the lack of allowance for direct feedback between the conditional variance and the conditional mean (Brooks, 2008). The Exponential GARCH (EGARCH) model is widely recognized as the most prevalent asymmetric GARCH model. The EGARCH model, initially proposed by Nelson (1991), expresses the conditional variance in a logarithmic format. The EGARCH model excels in capturing the leverage effect of financial time series, unlike the classic GARCH model, which cannot address this issue.

4.3 The Exponential GARCH (EGARCH) Model

In 1991, Nelson introduced the EGARCH model, which includes the variance equation expressed in logarithmic form. The EGARCH model is preferable for estimating the parameters of σ_t^2 since it does not impose any constraints on the model's parameters. Wang et al. (2022) provided a precise definition of the conditional variance as follows –

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^p \alpha_i \left| \frac{\mu_{t-i}}{\sigma_{t-i}} - E\left(\frac{\mu_{t-i}}{\sigma_{t-i}}\right) \right| + \sum_{j=1}^q \beta_j \ln(\sigma_{t-j}^2) + \sum_{k=1}^r \gamma_k \frac{\mu_{t-k}}{\sigma_{t-k}} \quad \dots\dots\dots(iv)$$

The variance σ_t^2 is always positive, irrespective of the sign of the coefficient on the right side of the equation. Thus, in contrast to the GARCH model, including the logarithmic conditional variance on the left side of the equation permits the coefficient to take negative values, thereby enhancing the flexibility of the solution process. The effect of the EGARCH model is measured by an exponential form instead of a quadratic form, as long as there are unsymmetrical terms $\gamma \neq 0$ in its equation.

4.4 Data analysis Techniques

Before analyzing the data, descriptive statistics displays the specific stylized facts of return series. The assumption of normality of the return series has been checked using the Jarque-Bera test. Prior to fitting a time series model, it is imperative to do the stationarity or unit root test on the time series data. For this objective, a total of two tests, specifically the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, have been employed. An autoregressive moving average, i.e., an ARMA(p,q) model, has been utilized to develop the mean equations for the two employed volatility models. For selecting the orders of the models, the researchers have chosen two popular model selection criteria, namely Schwarz's (1978) Bayesian information criterion (BIC) and Akaike's (1974) information criterion (AIC). The decision criteria are the BIC and AIC values; the smaller the values the better the model. Additionally, the researchers have also considered the log-likelihood values of the selected models. The performances of the employed models have been examined under three different error distributions: the Normal, Student-t, and Generalized error distribution (GED). This study utilized the statistical software E-views version 13 for data analysis purposes.

5. Stylized Facts and Preliminary Tests

The analysis includes 2307 observations of the daily closing prices of the DS30 index from January 1, 2015, to March 31, 2025. To see the initial trend in the data over time, a time series graphic was created in Figure 1. There is no discernible trend, seasonal rhythm, or cyclical pattern in the data; instead, it plainly displays fluctuations.

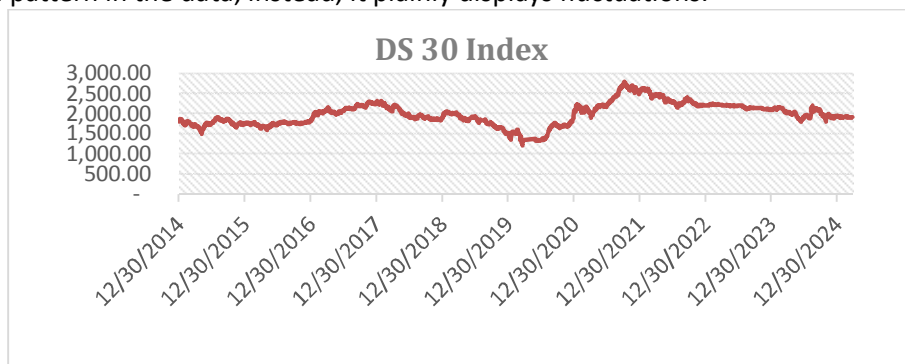


Figure 1: Daily data on DS30 index in raw form

5.1 Volatility Clustering

The daily returns from the DS30 index over the course of the study are displayed in Figure 2. This visual representation shows that the middle and ending periods of the sample had comparatively larger variations in returns. This series appears to exhibit volatility clustering, with small changes typically followed by little changes and substantial changes of either sign—usually after considerable modifications. The overall tendency for markets to experience periods of high and low volatility can also be used to characterize it (Taylor, 2005). It is the main sign that ARCH class models should be used to parameterize the volatilities of such data.

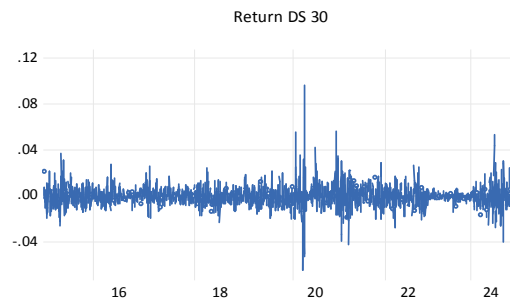


Figure 2: Depicts the daily data on DS30 index in return form

5.2 Descriptive Statistics of DS30 Index

Summary statistics for the DS30 index return of the total sample period are shown in Table 1. The index has a substantial difference between its lowest return of -6.40 percent and its best return of 9.68 percent. Its average return every day is 0.0027 percent. These results, along with the 0.87 percent standard deviation, show that the DS30 index companies' prices are subject to large price swings. The right tail is extreme when the skewness is positive (0.7962), indicating non-symmetric returns in such stocks. Once more, this index returns kurtosis of 15.72, far higher than the typical value of 3. This suggests that the returns are not symmetrical and have a non-normal distribution. Even at 1% significance, the Jarque Bera (JB) normality test statistic of 15793.28 decisively rejects the null hypothesis that the data has a normal distribution.

Table 1: Descriptive statistics on return data of DS30 index for the full period

Mean	2.68E-05	Kurtosis	15.71863
Median	-7.34E-05	Jarque-Bera	15793.28
Maximum	0.096847	Probability	0.0000
Minimum	-0.06395	Sum	0.06183
Std. Dev.	0.008679	Sum Sq. Dev.	0.173691
Skewness	0.796231	Observations	2307

Source: Authors' own calculation

5.3 Testing for Heteroscedasticity

Examining volatility characteristics of the DS30 index requires implementing the Lagrange Multiplier (LM) methodology to detect heteroscedasticity patterns (ARCH effects) within the residual components of daily return sequences. The analytical framework permits generation of appropriate residuals through various mean equation specifications—AR(p), MA(q), or ARMA(p,q)—selected according to contextual suitability (Savadatti, 2018). Table 1.3 displays a correlogram of squared residuals to facilitate the analysis. The null hypothesis cannot be rejected when the probability value is below 0.05 and accepted when the probability value exceeds this threshold. A test of the ARCH effect based on arbitrarily selected mean ARMA (1,1) has been conducted by regressing the squared residuals with arbitrarily selected lags of 5, 10, 15, 20, & 25. The LM test results showed in Table 2 confirm that the test statistic exceeds all critical values and demonstrates significance even at the 1% level. This statistical evidence provides robust justification for rejecting the composite null hypothesis positing non-significant squared residual coefficients, thereby confirming heteroscedastic patterns (ARCH effects) within the DS30 index daily return data. The correlogram of the squared residuals, shown in Table 3, also displays that all the autocorrelations and partial autocorrelations are also highly meaningful, signaling the presence of the ARCH effect in residuals. These validate that the ARCH/GARCH-type models can be applied to this return data for volatility estimation.

Table 2: Result of Heteroskedasticity test of daily return data on DS30 index

Lags		Return on DS30 index
5	LM stat	2.67E+10
	P-Value	0.0000
10	LM stat	2.19E+15
	P-Value	0.0000
15	LM stat	4.20E+10
	P-Value	0.0000
20	LM stat	4.50E+14
	P-Value	0.0000
25	LM stat	2.44E+11
	P-Value	0.0000

Source: Authors' own calculation

Table 3: Correlogram of squared residuals of daily DS30 index returns

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.212	0.212	104.09	0.000
		2	0.183	0.144	181.35	0.000
		3	-0.028	-0.098	183.14	0.000
		4	0.088	0.092	201.18	0.000
		5	-0.062	-0.081	210.04	0.000
		6	0.072	0.074	221.95	0.000
		7	-0.066	-0.067	232.12	0.000
		8	0.068	0.061	242.71	0.000
		9	-0.066	-0.056	252.73	0.000
		10	0.066	0.052	262.73	0.000
		11	-0.064	-0.048	272.35	0.000
		12	0.064	0.045	281.88	0.000
		13	-0.063	-0.042	291.09	0.000
		14	0.063	0.039	300.19	0.000
		15	-0.062	-0.036	308.99	0.000
		16	0.061	0.034	317.69	0.000
		17	-0.060	-0.032	326.10	0.000
		18	0.060	0.030	334.41	0.000
		19	-0.059	-0.028	342.45	0.000
		20	0.058	0.026	350.39	0.000
		21	-0.057	-0.024	358.07	0.000
		22	0.057	0.023	365.66	0.000
		23	-0.056	-0.021	373.00	0.000
		24	0.056	0.020	380.25	0.000
		25	-0.055	-0.019	387.27	0.000
		26	0.054	0.018	394.19	0.000
		27	-0.054	-0.017	400.90	0.000
		28	0.053	0.016	407.52	0.000
		29	-0.052	-0.015	413.93	0.000
		30	0.052	0.014	420.25	0.000
		31	-0.051	-0.013	426.38	0.000
		32	0.051	0.013	432.42	0.000
		33	-0.050	-0.012	438.28	0.000
		34	0.050	0.011	444.05	0.000
		35	-0.049	-0.010	449.65	0.000
		36	0.049	0.010	455.17	0.000

Source: Authors' own calculation

5.4 Testing for Stationarity

Stationarity properties of the DS30 index daily returns were evaluated through dual methodological approaches: the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) frameworks. The ADF implementation incorporated extended lag structures (up to 12 lags) of the dependent variable within return series regression equations. Both testing methodologies employed three distinct model specifications—constant-only, constant with trend, and neither constant nor trend—with comprehensive results presented in Table 4. The hypotheses of interest are H_0 : Series contains a unit root versus H_1 : Series is stationary. The critical values for both the ADF and PP tests at the level under all three equation specifications are less than the corresponding computed t-stat for the return series with probability values of 0, conclusively rejecting the unit root null hypothesis and confirming stationarity according to both tests. Therefore, the DS30 index daily return series exhibits stationarity at level.

Table 4: Unit root tests results

Items	Level/ Difference	Equation	ADF Test				PP Test				Comment
			Test-statistic	Critical Value		p-value	t-statistic	Critical Value		p-value	
				1% level	5% level			1% level	5% level		
DS 30 index	Level	Intercept	-25.37	-3.43	-2.86	0.000	-40.59	-3.43	-2.86	0.000	Stationary at level
		Trend & intercept	-25.36	-3.96	-3.41	0.000	-40.58	-3.96	-3.41	0.000	
		None	-25.37	-2.57	-1.94	0.000	-40.60	-2.57	-1.94	0.000	

Source: Authors' calculation

6. Construction of Mean Equation

Constructing appropriate mean equations represents a foundational element in volatility modeling through ARCH/GARCH methodologies. The ARMA(p,q) framework integrates AR(p) and MA(q) structures, establishing linear relationships between current series values and their historical observations, alongside current and lagged white noise error components (Brooks, 2008). The analytical approach explored model specifications across an extensive parameter space, encompassing combinations of ARMA(p,q) = (0,0) through (10,10). As mentioned earlier, during the model selection process, the results of the two commonly used information criteria—Akaike's (1974) information criterion (AIC) and Schwarz's (1978) Bayesian information criterion (BIC)—are displayed in Table 5, and Table 6, respectively.

“Of the two criteria, the BIC has superior large sample properties. However, in small samples, the AIC can work better than the BIC” (Enders, 2015). The BIC and AIC criteria indicate the ARMA (0,1) and ARMA (6,7) as the best models for the DS30 index return series, respectively, based on the BIC and AIC values displayed in Tables 5, and Table 6. ARMA (0,1) based on BIC has been regarded as a mean model for building ARCH/GARCH-type models and additional analyses. Since BIC usually chooses the lower-order model over AIC, the former is also better for larger samples, and our total observations are 2307. As a result, *rds30 c ma(1)* is the chosen mean model for the DS30 index return series.

Table 5: AIC based information criteria for ARMA models on DS30 index

p/q	0	1	2	3	4	5	6	7	8	9
0	-6.6554	-6.6842	-6.6850	-6.6854	-6.6872	-6.6877	-6.6892	-6.6907	-6.6913	-6.6908
1	-6.6811	-6.6854	-6.6846	-6.6878	-6.6879	-6.6874	-6.6892	-6.6906	-6.6904	-6.6908
2	-6.6834	-6.6846	-6.6864	-6.6925	-6.6916	-6.6915	-6.6911	-6.6912	-6.6913	-6.6906
3	-6.6868	-6.6882	-6.6910	-6.6916	-6.6908	-6.6908	-6.6907	-6.6904	-6.6904	-6.6899
4	-6.6872	-6.6875	-6.6911	-6.6911	-6.6908	-6.6914	-6.6927	-6.6925	-6.6931	-6.6893
5	-6.6884	-6.6876	-6.6916	-6.6908	-6.6938	-6.6929	-6.6926	-6.6893	-6.6925	-6.6913
6	-6.6881	-6.6885	-6.6910	-6.6927	-6.6929	-6.6924	-6.6941	-6.6973	-6.6965	-6.6934
7	-6.6911	-6.6904	-6.6901	-6.6894	-6.6923	-6.6917	-6.6972	-6.6944	-6.6963	-6.6955
8	-6.6905	-6.6897	-6.6911	-6.6901	-6.6893	-6.6923	-6.6965	-6.6903	-6.6959	-6.6952
9	-6.6898	-6.6902	-6.6923	-6.6895	-6.6916	-6.6909	-6.6926	-6.6954	-6.6953	-6.6927

Source: Authors' own calculation

Table 6: BIC based information criteria for ARMA models on DS30 index

p/q	0	1	2	3	4	5	6	7	8	9
0	-6.6530	-6.6768	-6.6751	-6.6729	-6.6722	-6.6703	-6.6692	-6.6683	-6.6664	-6.6609
1	-6.6737	-6.6755	-6.6721	-6.6729	-6.6705	-6.6675	-6.6668	-6.6657	-6.6630	-6.6609
2	-6.6734	-6.6721	-6.6714	-6.6751	-6.6717	-6.6691	-6.6662	-6.6638	-6.6614	-6.6582
3	-6.6744	-6.6733	-6.6736	-6.6717	-6.6684	-6.6659	-6.6633	-6.6605	-6.6581	-6.6551
4	-6.6722	-6.6700	-6.6712	-6.6687	-6.6659	-6.6640	-6.6629	-6.6601	-6.6582	-6.6519
5	-6.6709	-6.6677	-6.6692	-6.6659	-6.6664	-6.6630	-6.6602	-6.6544	-6.6552	-6.6514
6	-6.6682	-6.6661	-6.6661	-6.6653	-6.6630	-6.6601	-6.6592	-6.6600	-6.6567	-6.6510
7	-6.6687	-6.6655	-6.6627	-6.6595	-6.6600	-6.6568	-6.6599	-6.6546	-6.6540	-6.6507
8	-6.6656	-6.6623	-6.6612	-6.6577	-6.6545	-6.6549	-6.6566	-6.6480	-6.6511	-6.6479
9	-6.6624	-6.6603	-6.6599	-6.6546	-6.6543	-6.6510	-6.6503	-6.6506	-6.6480	-6.6429

Source: Authors' own calculation

6.1 Results of Model Estimation and Discussions

From Tables 7 to 12, the various order combinations of the GARCH(p,q) and EGARCH(p,q) models estimated under three error distributions—Normal Gaussian, Student's t, and Generalized Error Distribution (GED)—have been presented. The mean equation for all GARCH specifications across all three error distributions was determined to be ARMA (0,1), or MA(1), selected through the ARMA(p,q) process. The optimal model specifications are highlighted by bolded BIC and AIC values, representing the lowest values within each table. Notably, Schwarz's Bayesian Information Criterion (BIC) consistently selected more parsimonious models compared to Akaike's Information Criterion (AIC) for both GARCH and EGARCH specifications. The combinations selected by BIC have been recognized as more efficient models under all error distributions, aligning with the established principle that lower-order models generally outperform higher-order alternatives. Therefore,

GARCH(1,2), and EGARCH(1,1) models are selected as the optimal models under normal Gaussian error distribution. Under Student's *t* error distribution, GARCH(1,1), and EGARCH(1,1) are determined to be superior specifications. Similarly, under generalized error distribution (GED), GARCH(1,1), and EGARCH(1,1) have emerged as the most appropriate formulations.

The expected results from the selected models under the generalized error distribution (GED), the Student's *t* error distribution, and the normal Gaussian error distribution are shown in Tables 13, 14, and 15. All three error distributions' variance equation results, as displayed in Tables 13, 14, and 15, support the notion that all ARCH and GARCH coefficients are highly statistically significant. The importance of the GARCH and ARCH terms demonstrates that the lagged conditional variance and lagged squared error have a significant effect on the return volatility of the DS30 index. This suggests that historical volatility is useful to illustrate current volatility. For each of the chosen models under all error distributions, the total of the estimated GARCH and ARCH coefficients ($\alpha + \beta$) are found to be greater than unity. It suggests that for the DS30 index, volatility shocks are quite persistent (Abdalla, 2012). It seems like the effects of shocks never go away. The existence of a leverage impact in the return is confirmed by the fact that the λ (leverage term) of all three chosen EGARCH models under all the error distributions is negative and statistically significant. The existence of the leverage effect suggests that negative information will affect its conditional volatility more than positive information.

After those models had been constructed, the researchers found that the autocorrelations and partial autocorrelations for the best-fitted models were not statistically significant, indicating that there were no leftover ARCH effects. However, the nonexistence of any remaining ARCH effects is further confirmed by the formal ARCH-LM test results in Tables 13, 14, and 15. Yet the results of the normality test, histograms for all of the best-fitted models—which are not presented in this paper—show that the residuals are still not normally distributed for any of them, with statistically significant Jarque-Bera statistics and kurtosis values larger than three. These are the only drawbacks found in those best-fitted models.

6.2 Information Criteria for GARCH Models on DS30 Index (January 2015 to March 2025)

Table 7: GARCH (Normal Gaussian Error Distribution)

AIC									
p/q	1	2	3	4	5	6	7	8	9
1	-7.1074	-7.1133	-7.1129	-7.1145	-7.1136	-7.1138	-7.1196	-7.1181	-7.1175
2	-7.1072	-7.1082	-7.1088	-7.1134	-7.1158	-7.1103	-7.1207	-7.1233	-7.1223
3	-7.1064	-7.1077	-7.1112	-7.1125	-7.1140	-7.1157	-7.1220	-7.1218	-7.1210
4	-7.1138	-7.1129	-7.1199	-7.1172	-7.1178	-7.1176	-7.1208	-7.1185	-7.1164
5	-7.1130	-7.1123	-7.1184	-7.1174	-7.1155	-7.1144	-7.1122	-7.1034	-7.0984
6	-7.1162	-7.1163	-7.1166	-7.1164	-7.1165	-7.1132	-7.1110	-7.1055	-7.0747
7	-7.1165	-7.1165	-7.1209	-7.1245	-7.1133	-7.1130	-7.1132	-7.1078	-7.0954
8	-7.1140	-7.1133	-7.1193	-7.1167	-7.1171	-7.1161	-7.1143	-7.0982	-7.1074
9	-7.1177	-7.1168	-7.1185	-7.1167	-7.1238	-7.1204	-7.1245	-7.1132	-7.0981

Source: Authors' own estimation

BIC

p/q	1	2	3	4	5	6	7	8	9
1	-7.0949	-7.0984	-7.0955	-7.0946	-7.0912	-7.0889	-7.0922	-7.0882	-7.0851
2	-7.0923	-7.0907	-7.0888	-7.0909	-7.0909	-7.0829	-7.0909	-7.0910	-7.0875
3	-7.0890	-7.0878	-7.0888	-7.0876	-7.0866	-7.0859	-7.0897	-7.0869	-7.0837
4	-7.0939	-7.0905	-7.0950	-7.0898	-7.0879	-7.0852	-7.0859	-7.0812	-7.0766
5	-7.0906	-7.0874	-7.0910	-7.0875	-7.0831	-7.0795	-7.0749	-7.0636	-7.0561
6	-7.0913	-7.0889	-7.0867	-7.0841	-7.0817	-7.0759	-7.0712	-7.0632	-7.0299
7	-7.0891	-7.0866	-7.0885	-7.0897	-7.0759	-7.0732	-7.0709	-7.0630	-7.0481
8	-7.0842	-7.0809	-7.0845	-7.0794	-7.0772	-7.0737	-7.0695	-7.0509	-7.0949
9	-7.0853	-7.0820	-7.0812	-7.0769	-7.0814	-7.0756	-7.0772	-7.0635	-7.0459

Source: Authors' own estimation

Table 8: GARCH (Student's t Error Distribution)

AIC

p/q	1	2	3	4	5	6	7	8	9
1	-7.1545	-7.1543	-7.1539	-7.1585	-7.1563	-7.1582	-7.1639	-7.1465	-7.1472
2	-7.1542	-7.1553	-7.1555	-7.1431	-7.1400	-7.1398	-7.1454	-7.1639	-7.1639
3	-7.1534	-7.1549	-7.1546	-7.1422	-7.1420	-7.1512	-7.1613	-7.1480	-7.1479
4	-7.1579	-7.1571	-7.1622	-7.1615	-7.1439	-7.1607	-7.1631	-7.1475	-7.1459
5	-7.1581	-7.1562	-7.1607	-7.1616	-7.1462	-7.1439	-7.1454	-7.1444	-7.1454
6	-7.1616	-7.1608	-7.1572	-7.1546	-7.1508	-7.1493	-7.1450	-7.1426	-7.1412
7	-7.1609	-7.1606	-7.1611	-7.1643	-7.1635	-7.1445	-7.1431	-7.1455	-7.1378
8	-7.1605	-7.1600	-7.1443	-7.1447	-7.1425	-7.1429	-7.1457	-7.1438	-7.1359
9	-7.1609	-7.1600	-7.1445	-7.1639	-7.1633	-7.1640	-7.1446	-7.1403	-7.1373

BIC

p/q	1	2	3	4	5	6	7	8	9
1	-7.1396	-7.1369	-7.1339	-7.1361	-7.1314	-7.1308	-7.1340	-7.1141	-7.1123
2	-7.1368	-7.1354	-7.1331	-7.1182	-7.1126	-7.1099	-7.1131	-7.1291	-7.1265
3	-7.1335	-7.1325	-7.1297	-7.1148	-7.1121	-7.1189	-7.1264	-7.1107	-7.1080
4	-7.1355	-7.1322	-7.1348	-7.1316	-7.1115	-7.1258	-7.1257	-7.1077	-7.1036
5	-7.1332	-7.1288	-7.1308	-7.1292	-7.1113	-7.1065	-7.1056	-7.1021	-7.1005
6	-7.1342	-7.1309	-7.1248	-7.1197	-7.1134	-7.1095	-7.1027	-7.0978	-7.0939
7	-7.1310	-7.1282	-7.1262	-7.1270	-7.1237	-7.1021	-7.0983	-7.0981	-7.0880
8	-7.1281	-7.1251	-7.1069	-7.1048	-7.1002	-7.0981	-7.0984	-7.0940	-7.0836
9	-7.1261	-7.1227	-7.1046	-7.1216	-7.1185	-7.1167	-7.0948	-7.0880	-7.0825

Source: Authors' own estimation

Table 9: GARCH (Generalized Error Distribution)

AIC

p/q	1	2	3	4	5	6	7	8	9
1	-7.1541	-7.1589	-7.1574	-7.1589	-7.1586	-7.1562	-7.1595	-7.1005	-7.1576
2	-7.1539	-7.1548	-7.1548	-7.1578	-7.1574	-7.1536	-7.1582	-7.0698	-7.0957
3	-7.1531	-7.1542	-7.1536	-7.1518	-7.1503	-7.1550	-7.1604	-7.0595	-7.1245
4	-7.1583	-7.1575	-7.1608	-7.1611	-7.1594	-7.1589	-7.1587	-7.1252	-7.1047
5	-7.1575	-7.1567	-7.1604	-7.1589	-7.1558	-7.1542	-7.1461	-7.0942	-7.0571
6	-7.1598	-7.1593	-7.1603	-7.1598	-7.1542	-7.1424	-7.1412	-7.0877	-7.0619
7	-7.1595	-7.1591	-7.1620	-7.1634	-7.1606	-7.1378	-7.1411	-7.0925	-7.1169
8	-7.1578	-7.1584	-7.1599	-7.1628	-7.1612	-7.1617	-7.1486	-7.1475	-7.1352
9	-7.1570	-7.1587	-7.1626	-7.1613	-7.1546	-7.1476	-7.1504	-7.1525	-7.1206

BIC

p/q	1	2	3	4	5	6	7	8	9
1	-7.1391	N/A	-7.1375	-7.1364	-7.1337	-7.1288	-7.1296	-7.0682	-7.1227
2	-7.1365	-7.1349	-7.1324	-7.1329	-7.1300	-7.1237	-7.1258	-7.0349	-7.0583
3	-7.1331	-7.1318	-7.1287	-7.1244	-7.1204	-7.1226	-7.1255	-7.0222	-7.0847
4	-7.1359	-7.1326	-7.1334	-7.1312	-7.1271	-7.1241	-7.1213	-7.0854	-7.0624
5	-7.1326	-7.1293	-7.1305	-7.1265	-7.1209	-7.1168	-7.1063	-7.0519	-7.0122
6	-7.1324	-7.1295	-7.1279	-7.1249	-7.1169	-7.1026	-7.0988	-7.0428	-7.0146
7	-7.1296	-7.1268	-7.1271	-7.1260	-7.1208	-7.0955	-7.0963	-7.0452	-7.0671
8	-7.1254	-7.1235	-7.1225	-7.1230	-7.1188	-7.1169	-7.1013	-7.0977	-7.0829
9	-7.1221	-7.1214	-7.1228	-7.1190	-7.1098	-7.1003	-7.1006	-7.1002	-7.0658

Source: Authors' own estimation

6.3 Information Criteria for EGARCH Models on DS30 Index (January 2015 to March 2025)

Table 10: EGARCH (Normal Gaussian Error Distribution)

AIC

p/q	1	2	3	4	5	6	7	8	9
1	-7.1275	-7.1275	-7.1267	-7.1322	-7.1344	-7.1359	-7.1413	-7.1247	-7.1411
2	-7.1271	-7.1216	-7.1283	-7.1313	-7.1361	-7.1345	-7.1412	-7.1332	-7.1410
3	-7.1262	-7.1259	-7.1257	-7.1276	-7.1410	-7.1348	-7.1013	-7.1247	-7.1315
4	-7.1305	-7.1300	-7.1344	-7.1344	-7.1409	-7.1268	-7.1367	-7.1426	N/A
5	-7.1323	-7.1358	-7.1349	-7.1336	-7.1352	-7.1406	-7.1320	-7.0916	-7.1325
6	-7.1370	-7.1363	-7.1354	-7.1376	-7.1367	N/A	-7.1402	-7.1395	-7.1502
7	-7.1362	-7.1362	-7.1345	-7.1407	-7.1359	-7.1358	-7.1453	-7.1464	-7.1437
8	-7.1354	-7.1349	-7.1353	-7.1400	-7.1395	-7.1378	-7.1488	N/A	-7.1414
9	-7.1361	-7.1365	-7.1318	-7.1348	-7.1355	-7.1315	-7.1484	-7.0950	-7.1456

Source: Authors' own estimation

BIC

p/q	1	2	3	4	5	6	7	8	9
1	-7.1126	-7.1101	-7.1068	-7.1098	-7.1095	-7.1085	-7.1114	-7.0923	-7.1062
2	-7.1097	-7.1017	-7.1059	-7.1064	-7.1087	-7.1046	-7.1089	-7.0984	-7.1036
3	-7.1063	-7.1035	-7.1009	-7.1002	-7.1112	-7.1024	-7.0664	-7.0874	-7.0916
4	-7.1081	-7.1051	-7.1070	-7.1046	-7.1085	-7.0920	-7.0994	-7.1028	N/A
5	-7.1074	-7.1084	-7.1051	-7.1012	-7.1004	-7.1033	-7.0921	-7.0493	-7.0876
6	-7.1096	-7.1064	-7.1031	-7.1027	-7.0994	N/A	-7.0978	-7.0947	-7.1029
7	-7.1064	-7.1064	-7.0997	-7.1034	-7.0961	-7.0935	-7.1005	-7.0991	-7.0939
8	-7.1030	-7.1001	-7.0980	-7.1002	-7.0972	-7.0930	-7.1015	N/A	-7.0891
9	-7.1012	-7.0992	-7.0920	-7.0925	-7.0907	-7.0842	-7.0986	-7.0427	-7.0908

Source: Authors' own estimation

Table 11: EGARCH (Student's t Error Distribution)

AIC

p/q	1	2	3	4	5	6	7	8	9
1	-7.1737	-7.1736	-7.1703	-7.1764	-7.1788	-7.1790	-7.1823	-7.1815	-7.1815
2	-7.1734	-7.1727	-7.1738	-7.1757	-7.1796	-7.1788	-7.1774	-7.1812	-7.1806
3	-7.1726	-7.1725	-7.1731	-7.1748	-7.1736	-7.1779	-7.1804	N/A	-7.1783
4	-7.1744	-7.1742	-7.1776	-7.1777	-7.1768	-7.1760	-7.1811	-7.1808	-7.1799
5	-7.1770	-7.1656	-7.1786	-7.1769	-7.1797	-7.1739	-7.1813	-7.1727	-7.1805
6	-7.1802	-7.1794	-7.1787	-7.1801	-7.1752	-7.1688	-7.1816	-7.1756	-7.1777
7	-7.1794	-7.1786	-7.1782	-7.1818	-7.1809	-7.1798	-7.1808	-7.1828	-7.1789
8	-7.1787	-7.1779	-7.1784	-7.1785	-7.1798	-7.1789	-7.1871	-7.1892	-7.1752
9	-7.1793	-7.1735	-7.1776	-7.1800	N/A	-7.1802	-7.1819	-7.1746	-7.1774

BIC

p/q	1	2	3	4	5	6	7	8	9
1	-7.1562	-7.1537	-7.1479	-7.1515	-7.1514	-7.1491	-7.1500	-7.1466	-7.1442
2	-7.1535	-7.1503	-7.1489	-7.1483	-7.1497	-7.1464	-7.1425	-7.1439	-7.1408
3	-7.1502	-7.1476	-7.1457	-7.1449	-7.1412	-7.1430	-7.1430	N/A	-7.1359
4	-7.1495	-7.1468	-7.1477	-7.1453	-7.1420	-7.1387	-7.1413	-7.1385	-7.1351
5	-7.1496	-7.1357	-7.1462	-7.1420	-7.1424	-7.1341	-7.1390	-7.1279	-7.1332
6	-7.1504	-7.1470	-7.1439	-7.1427	-7.1354	-7.1264	-7.1368	-7.1283	-7.1279
7	-7.1470	-7.1437	-7.1409	-7.1419	-7.1385	-7.1350	-7.1335	-7.1330	-7.1266
8	-7.1439	-7.1406	-7.1386	-7.1362	-7.1350	-7.1316	-7.1373	-7.1369	-7.1204
9	-7.1419	-7.1336	-7.1353	-7.1352	N/A	-7.1304	-7.1296	-7.1199	-7.1202

Source: Authors' own estimation

Table 12: EGARCH (Generalized Error Distribution)

AIC

p/q	1	2	3	4	5	6	7	8	9
1	-7.1715	-7.1715	-7.1706	-7.1702	-7.1761	-7.1757	N/A	N/A	N/A
2	-7.1713	-7.1707	-7.1713	-7.1731	-7.1768	N/A	-7.1788	-7.1708	-7.1741
3	-7.1704	-7.1702	-7.1699	-7.1723	-7.1760	-7.1752	-7.1786	-7.1698	-7.1757
4	-7.1726	-7.1723	-7.1751	-7.1750	-7.1734	-7.1732	-7.1788	-7.1782	-7.1855
5	-7.1745	-7.1765	-7.1759	-7.1742	-7.1734	-7.1784	-7.1718	-7.1783	-7.1675
6	-7.1774	-7.1766	-7.1757	-7.1766	-7.1758	-7.1813	-7.1792	-7.1783	-7.1709
7	-7.1765	-7.1758	-7.1749	-7.1788	-7.1780	-7.1761	-7.1667	-7.1790	-7.1739
8	-7.1757	-7.1749	-7.1755	-7.1757	-7.1770	-7.1762	-7.1811	-7.1601	-7.1864
9	-7.1762	-7.1760	-7.1742	-7.1751	-7.1744	-7.1829	-7.1762	-7.1759	-7.1676

BIC

p/q	1	2	3	4	5	6	7	8	9
1	-7.1541	-7.1516	-7.1482	-7.1453	-7.1487	-7.1458	N/A	N/A	N/A
2	-7.1513	-7.1483	-7.1464	-7.1458	-7.1469	N/A	-7.1440	-7.1334	-7.1342
3	-7.1480	-7.1453	-7.1425	-7.1424	-7.1436	-7.1403	-7.1413	-7.1300	-7.1334
4	-7.1477	-7.1449	-7.1452	-7.1426	-7.1386	-7.1359	-7.1390	-7.1359	-7.1407
5	-7.1471	-7.1466	-7.1435	-7.1393	-7.1361	-7.1385	-7.1295	-7.1335	-7.1202
6	-7.1475	-7.1442	-7.1409	-7.1393	-7.1359	-7.1390	-7.1344	-7.1310	-7.1211
7	-7.1442	-7.1409	-7.1376	-7.1390	-7.1356	-7.1313	-7.1194	-7.1293	-7.1217
8	-7.1409	-7.1375	-7.1357	-7.1334	-7.1322	-7.1289	-7.1313	-7.1078	-7.1317
9	-7.1389	-7.1361	-7.1319	-7.1303	-7.1271	-7.1331	-7.1239	-7.1211	-7.1104

Source: Authors' own estimation

Table 13: Estimated results of GARCH-type models following Normal Gaussian error distribution

Coefficients	MA (1)-GARCH (1,2)	MA (1)-EGARCH (1,1)
Mean Equation		
ω	7.89E-05	-2.11E-04
ma (1)	0.187601***	0.182787***
Variance Equation		
α_0 (constant)	7.24E-07***	-0.581724***
α_1 (ARCH term)	0.135223***	0.321741***
β_1 (GARCH term)	1.360587***	0.965902***
β_2 (GARCH term)	0.486952***	
λ_1 (leverage term)		-0.03969***
$\alpha + \beta$	1.009	1.287643
AIC	-7.113303	-7.127528
BIC	-7.098365	-7.11259
Log likelihood	8211.195	8227.604

ARCH-LM Test for Heteroscedasticity (with lag 5)		
LM-Statistic	1.379728	2.064155
Probability	0.2287	0.0671
Desirable findings in autocorrelation tests	Yes	Yes
Desirable findings in normality tests in residuals	No	No

Remark: ***, ** mark significance at the 1%, and 5% level respectively

Table 14: Estimated results of chosen GARCH-type models following Student's t error distribution

Coefficients	MA (1)-GARCH (1,1)	MA (1)-EGARCH (1,1)
Mean Equation		
ω	-6.65E-05	-1.90E-04
ma (1)	0.187240***	0.180824***
Variance Equation		
α_0 (constant)	4.86E-07***	-0.508209***
α_1 (ARCH term)	0.176150***	0.311959***
β_1 (GARCH term)	0.840375***	0.972477***
λ_1 (leverage term)		-0.04544***
$\alpha + \beta$	1.017	1.2844
AIC	-7.154548	-7.173661
BIC	-7.13961	-7.156233
Log likelihood	8258.771	8281.818
ARCH-LM Test for Heteroscedasticity (with lag 5)		
LM-Statistic	1.459895	2.01633
Probability	0.1998	0.0734
Desirable findings in autocorrelation tests	Yes	Yes
Desirable findings in normality tests in residuals	No	No

Remark: ***, ** mark significance at the 1%, and 5% level respectively

Table 15: Contains the estimated results of selected GARCH-type models under Generalized error distribution

Coefficients	MA (1)-GARCH (1,2)	MA (1)-EGARCH (1,1)
Mean Equation		
ω	-6.95E-05	-1.76E-04
ma (1)	0.170648***	0.171785***

Variance Equation		
α_0 (constant)	6.67E-07***	-0.54776***
α_1 (ARCH term)	0.180246***	0.316425***
β_1 (GARCH term)	0.830471***	0.968985***
λ_1 (leverage term)		-0.042105***
$\alpha + \beta$	1.011	1.2854
AIC	-7.154084	-7.17153
BIC	-7.139146	-7.154102
Log likelihood	8258.236	8279.359
ARCH-LM Test for Heteroscedasticity (with lag 5)		
LM-Statistic	1.633816	2.064002
Probability	0.1476	0.0671
Desirable findings in autocorrelation tests	Yes	Yes
Desirable findings in normality tests in residuals	No	No

Remark: ***, ** represents significant at the 1%, and 5% level respectively

6.4 Model Comparison

Empirical evidence demonstrates differential model performance across distributional frameworks: under Normal Gaussian assumptions, GARCH(1,2) and EGARCH(1,1) configurations exhibit optimal characteristics. Within Student's t distributional contexts, both GARCH(1,1), and EGARCH(1,1) specification emerge as preferred specifications. Similarly, Generalized error distributional implementation reveals GARCH(1,1) and EGARCH(1,1) as superior formulations. While all examined models demonstrate adequacy for DS30 index volatility characterization, as evidenced in Tables 4.1, 4.2, and 4.3, maximum log likelihood criteria identify MA(1)-GARCH(1,1), and MA(1)-EGARCH(1,1) under Student's t distributional assumptions as superior specifications. This analytical finding maintains consistency regardless of model symmetry characteristics; highlighting the critical importance of distributional assumption selection in DS30 index volatility modelling endeavors.

7. Conclusion

This research investigated whether the selection of optimal model specifications for the 30 blue-chip stocks comprising the DS30 index from the Dhaka Stock Exchange Ltd., Bangladesh, is influenced by the choice of error distribution. To address this research question, Generalized Autoregressive Conditional Heteroscedastic (GARCH) and Exponential GARCH (EGARCH) models were estimated under three error distributions: Normal Gaussian, Student's t, and Generalized error distribution. The findings reveal that GARCH(1,2) and EGARCH(1,1) constitute optimal specifications following a normal Gaussian

error distribution. Under Student's t error distribution, GARCH(1,1), and EGARCH(1,1) have been identified as superior models. Similarly, under Generalized error distribution (GED), GARCH(1,1), and EGARCH(1,1) have emerged as the most appropriate formulations. Importantly, the Student's t error distribution consistently yielded superior models, regardless of whether symmetric or asymmetric GARCH formulations were employed. Thus, it is evident that picking the right error distributions has significance for modelling the volatility of the DS30 index. However, a few more models from the ARCH/GARCH family and a few more error distributions can be utilized for further research.

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