



GARCH Model for Evaluating Volatility Based on the Share Price of Airlines Company During the COVID-19 Outbreak

Nashirah Abu Bakar¹, Sofian Rosbi², Kiyotaka Uzaki³

¹Islamic Business School, College of Business, Universiti Utara Malaysia, 06010 Sintok, Kedah, Malaysia

²Faculty of Business & Communication, Universiti Malaysia Perlis, 01000 Kangar, Perlis, Malaysia

³Department of Business Management Systems, Faculty of Economics, Oita University, Japan

Abstract: The COVID-19 outbreak has affected economic activities in the worldwide financial market. The instability of financial markets makes investors uncomfortable because there is not enough study to prove the volatility of share price movements. One of the most affected sectors is tourism namely airlines company. Therefore, this study is implemented to analyze the volatility rate for the share price of financial markets based on airlines company. This study uses one sample of companies from Malaysia Stock Exchange for an airline company that was affected by the COVID-19 outbreak. Data were collected from February 2020 until June 2022. The number of daily observations is 545 days. The distribution of return rate data follows non-normal distribution according to Jarque-Bera statistical test. Next, this study performed three types of unit root tests namely ADF, PP, and KPSS. All three statistical tests agreed that the return data achieved stationarity characteristics at the level. The mean equation for this study is using ARMA (2,2). Then, this study uses Generalized Auto-Regressive Conditional Heteroskedasticity (GARCH) for modeling volatility. The result shows there is high volatility clustering that exists during the COVID-19 outbreak. The value of AIC, SC, and HQN show the fittest model is TGARCH (1,1). The threshold effect is positive and significant. Therefore, the bad news is likely to be pronounced rather than the good news. Thus, it is important to investors in carefully evaluate their investment strategy to reduce their investment risk. The findings of this study help the government to develop suitable policies in assisting the economic and financial stability

Keywords: COVID-19, Volatility, GARCH model, Airlines company, Investment

1. Introduction

The emerging market is currently faced with weak growth economic due to the spread of the COVID-19 virus since 2019. Stock market performance is recorded a significant decline due to the spread of the COVID-19 virus which give an impact on investors and market behavior. In the current stock market climate, uncertainty and volatility are critical factors that give impact towards investors' decisions and market behavior (Akinlaso, et al., 2022). Thus, volatility forecasting has gained significant importance in the investigation due to the COVID-19 pandemic. COVID-19 virus gives a negative impact on the growth of the economy worldwide. Even though the COVID-19 pandemic reached the endemic due to most people getting a vaccine, overcoming the losses faced during the COVID-19 outbreak still needs a lot of suggestions, planning, and improvement.

Thus, most researchers investigated the impact of COVID-19 on economic growth (Abu Bakar and Rosbi, 2021a; Abu Bakar and Rosbi, 2021b). Mobin, et al., (2022) confirmed that bad news about the COVID-19 pandemic is causing higher volatility. They found that the Canadian stock and bond markets are the most volatile, and Italian bond and stock markets are the most sensitive G7 countries. Japan has shown the highest persistence, and the stock market exhibits higher leverage than the bond market.

A study by Ghorbel and Jeribi (2021) regarding the relationship between the volatilities of oil, the Chinese stock index, and financial assets (cryptocurrency, gold, and G7 stock indexes) found that all variables display strong volatility

concentrated in the first four months of Covid-19 outbreak. During the first quarter of 2020, stock markets worldwide recorded significant turmoil in response to the emergence of the COVID-19 virus (Akinlaso, et al., 2022).

This study aims to investigate the volatility rate for the share price of the airline industry in Malaysia. Even though there are many types of research regarding volatility, the study that focuses on the volatility for a specific industry is still lacking research. The performance of the airline industry dropped significantly. As suggested by Vinod (2021) airline industry need to adopt a new marketing planning process of scheduling, pricing, and revenue management that is nimbler to adapt quickly to changing market conditions.

During the COVID-19 pandemic, most governments of were implemented a lockdown approach to reduce the spread of the COVID-19 virus. Malaysia implemented a lockdown approach, consequently, the airline industry stopped its operations. Therefore, the financial performance of the airline industry declined significantly. COVID-19 outbreak also hampered the tourism industry with an impact on the all-others tourism-reliant sectors such as hotels, restaurants, travel agencies, and the transport sector massively suffered due to the global lockdown policy (Jafari, et al., 2021).

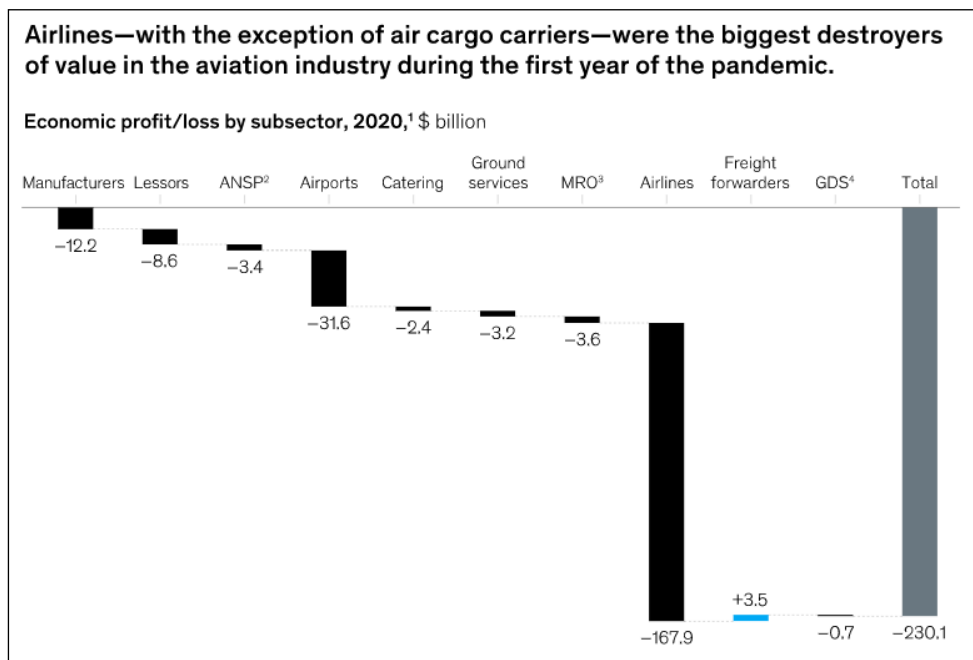


Figure 1: Airline Industry was the biggest destroyer
Sources: McKinsey’s Analysis (2022)

Figure 1 shows the airline industry was the biggest destroyer during the COVID-19 pandemic. According to Sheikh Yahya (2020), Malaysia’s aviation industry is losing RM13 billion in the year 2020 as air travel continues to face travel restrictions. Thus, the airline industry needs to plan a new strategy to overcome the loss during the COVID-19 pandemic to attract more passengers to use their services. However, in the year 2022 most countries started opening their border to allow more tourists to visit their countries. This situation gives a new opportunity for the airline industry to recover from the loss that happened during the COVID-19 outbreak.

Consequently, most of the airline industry was start their operation. Many promotions are done by the airline industry to promote their services. Therefore, the main objective of this paper is to examine the market volatility of the airline industry using the GARCH model. The GARCH model is one of the important models used to measure the volatility of the stock price (Abu Bakar and Rosbi, 2022). According to Paul and Sharma (2018), GARCH models are frequently used for estimating conditional moments of the return’s distribution, which are subsequently used to forecast conditional quantiles.

2. Literature Review

The unprecedented global health fear’s spread because of over 3.03 million deaths and 142.10 million confirmed cases resulting from the global outbreak of COVID-19 in Wuhan, China, has generated a new health crisis globally (Rubbianiy,

et al., 2022). All the industries in the world were affected by the spread of the COVID-19 outbreak. Obayelu, et al., (2021) highlights that the COVID-19 outbreak affected several aspects of international trade and led to a deep fall in transactions at the international and within-regions levels. While, Chua, et al., (2022) also mention that the COVID-19 outbreak has negatively affected the global economy, change the global trade network and contribute to the sharp decline in demand for oil.

Many industries in Malaysia were lost during the lockdown approach implemented by the Government of Malaysia in March 2020 (Abu Bakar and Rosbi, 2020a; Abu Bakar and Rosbi, 2020b; Abu Bakar and Rosbi, 2020c). In attempts to contain the spread of the virus, countries worldwide, including Malaysia, have implemented several containment measures, such as social distancing, mobile software applications for digital contact tracing (MySejahtera in Malaysia), lockdowns, and travel bans (Aldhamari, et al., 2022) to avoid the spread of COVID-19 virus. According to Abu Bakar, et al., (2022) COVID-19 give a bad impact on hotel tourism. This is because the airline industry stopped its operation. Numerous studies mentioned that the airline industry was the hardest hit during the COVID-19 pandemic (Skare, et al., 2021; Wen, et al., 2021; Zubair and Shamsudin, 2021). A previous study also confirmed that the COVID-19 outbreak has an impact on the stock market performance (Gherghina, et al., 2020).

A study by Harjoto and Rossi (2021) found that the COVID-19 pandemic had a significantly greater negative impact on the stock markets in emerging countries than in developed countries. Rakshit and Neog (2022) suggested that the central bank's effort is needed to maintain a stabilizing effect on the exchange rate and emphasis should also be given to boosting investors' confidence in the stock market. While Mushafiq (2021) found that industries in the Pakistan Stock Exchange were overall negatively affected by the COVID-19 outbreak.

The other researchers indicate the presence of volatility in the dependent variables arising out of economic policy uncertainty considering the segmentation of the study period into pre-COVID-19 and COVID-19. The results show that the variables move significantly from a low-volatility regime to a high-volatility regime due to the presence of COVID-19 (Ghosh, et al., 2022).

Studies that focus on the GARCH model suggested that the GARCH model is one of the most important methods in examining the volatility of share prices. This model will help investors to determine the price and potentially provide higher returns, as well as forecast the returns of investments. Gokcan, (2000), suggested that the GARCH model can be used for modeling volatility of time series data and found that the emerging stock markets GARCH (1,1) model performs better than the EGARCH model, even if the stock market return series display skewed distributions.

The (GARCH) model was generated by Bollerslev's (1986) response to stylized facts (Liu and Hung, 2010). In practice, a common assumption in applying GARCH models to financial data is that the return series is conditionally normally distributed. It is referred to as the normal GARCH model, which is well known as part of the volatility clustering patterns typically exhibited in financial and economic time series (Ghahramani and Thavaneswaran, 2006).

The literature study shows that there have been many studies that have attempted to model conditional volatility in emerging markets using the GARCH model. Handika and Chalid (2018) find that the best-fitted GARCH model tends to generate the best empirical performance for the most commodities market. GARCH models are frequently used for estimating conditional moments of the return's distribution, which are subsequently used to forecast conditional quantiles (Paul and Sharma, 2018).

Sharma and Vipul (2015) found that the standard GARCH model outperforms the more advanced GARCH models and provides the best one-step-ahead forecasts of the daily conditional variance. Volatility is one of the most significant features of the stock market, directly linked to market uncertainties, influencing the investment behavior of the firms (Kashyap, 2022).

Watanabe (2012), investigating the volatility of the S&P 500 stock index found that the realized GARCH model with the skewed Student's t-distribution performs better than that with the normal and Student's t-distributions and the exponential GARCH model using the daily returns only. In addition, Hansen et al., (2012) also found that a simple Realized GARCH structure leads to substantial improvements in the empirical fit over standard GARCH models that only use daily returns. Paul and Sharma (2018) also found that the Realized GARCH-EVT models generally outperform the standard GARCH-

EVT and EGARCH-EVT models. Therefore, the GARCH model is a suitable model in analyze the volatility of the stock market as suggested by researchers.

3. Methodology

This study aims to measure the volatility of share prices of airlines company in Malaysia. This study employed the Jarque-Bera test for testing the normality of data. Next, this study performed stationarity checking using the unit root test of ADF, PP, and KPSS. This study uses the autoregressive moving average (ARMA) model for the mean equation. In modeling the variance, the study uses the GARCH model, GARCH-Mean model, and Exponential GARCH model.

3.1 Normality Distribution Checking using Jarque-Bera Statistical Test

The goodness of fit test, the Jarque-Bera test is to measure if sample data has skewness and kurtosis that are similar to a normal distribution. The Jarque-Bera test statistic is always positive, and if it is not close to zero, it shows that the sample data do not have a normal distribution. If the data comes from a normal distribution, the JB statistic asymptotically has a chi-squared distribution with two degrees of freedom, so the statistic can be used to test the hypothesis that the data are from a normal distribution. The null hypothesis is a joint hypothesis of the skewness being zero and the excess kurtosis being zero. Samples from a normal distribution have an expected skewness of 0 and an expected excess kurtosis of 0.

The equation for the Jarque-Bera test is represented by Equation (1). the Jarque-Bera test is a goodness-of-fit test of whether sample data have the skewness and kurtosis matching a normal distribution. The value for the Jarque-Bera test statistic is always non-negative. If it is far from zero, it signals the data do not have a normal distribution.

$$JB = \frac{n}{6} \left(S^2 + \frac{1}{4} (K - 3)^2 \right) \dots\dots\dots (1)$$

Equation (1) explains the parameters as follows.

n : number of observations,

S : Sample skewness calculated using Equation (2).

$$S = \frac{\hat{\mu}_3}{\hat{\sigma}^3} = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^3}{\left(\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 \right)^{3/2}} \dots\dots\dots (2)$$

K : Sample kurtosis calculated using Equation (3).

$$K = \frac{\hat{\mu}_4}{\hat{\sigma}^4} = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^4}{\left(\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2 \right)^2} \dots\dots\dots (3)$$

The parameter $\bar{x}$ is the sample mean and x_i is the value of variable x at the observation period of t .

3.2 Unit Root Test

The unit root test evaluates whether a time series variable is non-stationary and possesses a unit root. This study uses three types of unit root tests namely the Augmented Dickey-Fuller (ADF) test, Philips-Perron (PP) test, and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test.

An augmented Dickey-Fuller test (ADF) defines the null hypothesis that a unit root is present in a time series sample. The unit root test is then carried out under the null hypothesis $\gamma = 0$ against the alternative hypothesis of $\gamma < 0$. Once a value for the test statistic is shown in Equation (4).

$$DF_{\tau} = \frac{\hat{\gamma}}{SE(\hat{\gamma})} \dots\dots\dots(4)$$

If the calculated test statistic is less (more negative) than the critical value, then the null hypothesis $\gamma = 0$ is rejected and no unit root is present.

Next, the second type of unit root test is Philips-Perron (PP) test. The PP test is used in time series analysis to test the null hypothesis that a time series is integrated of order 1. the Phillips–Perron test makes a non-parametric correction to the t-test statistic. The test is robust concerning unspecified autocorrelation and heteroscedasticity in the disturbance process of the test equation.

Then, the third type of unit root test is Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. KPSS test is used for testing a null hypothesis that an observable time series is stationary around a deterministic trend against the alternative of a unit root. KPSS test, the absence of a unit root is not a proof of stationarity but, by design, of trend-stationarity. This is an important distinction since it is possible for a time series to be non-stationary and have no unit root yet be trend-stationary.

3.3 Autoregressive Moving Average (ARMA) Model

An Autoregressive Moving Average (ARMA) model, is used to describe weakly stationary stochastic time series in terms of two polynomials. The first of these polynomials is for autoregression, and the second for the moving average. This is a model that is combined from the autoregressive (AR) and moving average (MA) models. In this model, the impact of previous lags along with the residuals is considered for forecasting the future values of the time series.

The autoregressive moving average model for order two can be written as shown in Equation (5).

$$y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \varepsilon_t \dots\dots\dots(5)$$

The parameters in Equation (5) are described as follows.

y_t : the value of a variable y at the observation period of t

y_{t-1} : the value of a variable y at the observation period of $t-1$, also known as the lag value of order one

y_{t-2} : the value of a variable y at the observation period of $t-2$, also known as the lag value of order two

μ : intercept or constant value

ε_t : error term at period t

ε_{t-1} : past shock at period $t-1$

ε_{t-2} : past shock at period $t-2$

The autoregressive model is considered using stationary data, in which case some constraints on the values of the parameters are required. For the AR component, the value of the coefficient of one lag variable should follow the below requirement.

$$-1 < f_t < 1 \dots\dots\dots(6)$$

This value is considered that series follow stationary characteristics.

3.4 Diagnostics Checking

This study performed two types of tests for assessing serial autocorrelation and heterogeneity problem. The first test is the Ljung-Box Q-statistics test to check for autocorrelation problems. The Ljung-Box Q (LBQ) statistic tests the null hypothesis that autocorrelations up to lag k equal zero. Equation (7) shows the error equation for detecting autocorrelation problems.

$$\hat{e}_t = r_1 \hat{e}_{t-1} + r_2 \hat{e}_{t-2} + \dots + r_p \hat{e}_{t-p} + v_t \dots\dots\dots(7)$$

For the autocorrelation testing, the conditions are described as follows.

$$H_0 : r_1 = r_2 = \dots = r_s = 0 \text{ (no autocorrelation problem)}$$

$$H_1 : r_1 \in r_2 \in \dots \in r_s \in 0 \text{ (autocorrelation problem exists)}$$

Q-statistics is represented using Equation (8).

$$Q = n(n+2) \sum_{k=1}^s \frac{\hat{p}_k^2}{(n-k)} : c_{s-(p+q)}^2 \dots \dots \dots (8)$$

Where, n is sample size, $\hat{p}_k$ is sample autocorrelation at lag k , and s is the number of lags being tested. Under null hypothesis assumption, the statistic Q asymptotically follows a c_s^2 .

Next, the heteroscedasticity is checked using Ljung-Box Q-squared statistics. The equation for checking heteroscedasticity which is non-constant variance is shown in Equation (9).

$$\hat{e}_t^2 = r_1 \hat{e}_{t-1}^2 + r_2 \hat{e}_{t-2}^2 + \dots + r_p \hat{e}_{t-p}^2 \dots \dots \dots (9)$$

For the heteroscedasticity testing, the conditions are described as follows.

$$H_0 : r_1 = r_2 = \dots = r_s = 0 \text{ (no heteroscedasticity problem)}$$

$$H_1 : r_1 \in r_2 \in \dots \in r_s \in 0 \text{ (heteroscedasticity problem exists)}$$

Q-squared-statistics is represented using Equation (10).

$$Q^2 = n(n+2) \sum_{k=1}^s \frac{\hat{p}_k^2}{(n-k)} : c_{s-(p+q)}^2 \dots \dots \dots (10)$$

3.5 Generalized Autoregressive Conditional Heteroscedasticity (GARCH)

Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) is a statistical model used in analyzing time-series data where the variance error is believed to be serially autocorrelated. GARCH models assume that the variance of the error term follows an autoregressive moving average process. GARCH is a statistical modeling technique used to help predict the volatility of returns on financial assets. GARCH is useful to assess risk and expected returns for assets that exhibit clustered periods of volatility in returns.

Next, the model of GARCH (1,1) is represented using Equation (11).

$$s_t^2 = w + a_1 e_{t-1}^2 + b_1 s_{t-1}^2 \dots \dots \dots (11)$$

The parameters in Equation (7) are described as follows.

e_{t-1}^2 : Past news about conditional variance

s_{t-1}^2 : Past conditional variance

Where, $w > 0, a_1 > 0, b_1 \geq 0, (a_1 + b_1) < 1$.

Then, this study uses threshold-asymmetric GARCH for analyzing asymmetric volatilities arising mainly from financial time series. In this threshold model, the state of the world which is determined by an observable threshold variable is therefore known, while conditional variance follows a GARCH process within each state. This model can be viewed as a special case of the random coefficient GARCH model.

The TGARCH (1,1) can be represented using Equation (12).

$$s_t^2 = w + a_1 e_{t-1}^2 + b_1 s_{t-1}^2 + t d_{t-1} e_{t-1}^2 \dots \dots \dots (12)$$

$$d_{t-1} = \begin{cases} 1, & \text{if } e_{t-1} < 0 \text{ (bad news)} \\ 0, & \text{if } e_{t-1} \geq 0 \text{ (good news)} \end{cases}$$

The parameter of t indicates the threshold effect. The sign is expected to be positive and significant so that bad news is likely pronounced rather than good news.

4. Result and Discussion

This section describes data selection and calculation for a return rate. Next, this section describes the unit root test in testing the data stationarity characteristics. Then, in evaluating the volatility, this study evaluated the GARCH model including GARCH-M and EGARCH.

4.1 Data Selection

This study selected the share price of one airline’s company on Malaysia Stock Exchange to assess the impact of the COVID-19 outbreak on the financial market. The selection of data starts from February 2020 until June 2022. The number of daily observations is 545 days.

Figure 2 shows the dynamic movement of share prices for an airline company in Malaysia. The value of the share price on the first-day observation is MYR 1.16. Due to the COVID-19 outbreak, the share price keeps decreasing until reached MYR 0.705 on the last observation.

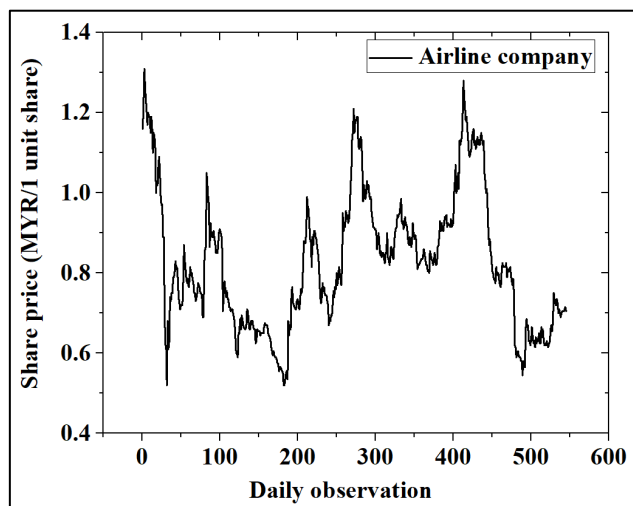


Figure 2: Share price movement for an airlines company in Malaysia

Next, this study calculated the return based the Equation (8).

$$r_t = \frac{\log \frac{y_t}{y_{t-1}}}{\log 3} \times 100\% \dots \dots \dots (8)$$

Where y_t is share price at observation t , and y_{t-1} is the share price at observation $t-1$.

Figure 3 shows the volatility behavior of an airline company in Malaysia. Figure 2 shows there is volatility clustering.

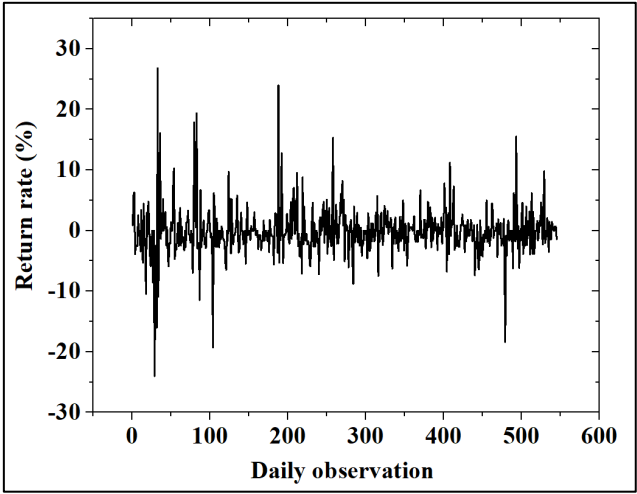


Figure 3: Return rate for the share price of an airlines company in Malaysia

Then, this study analyzed the descriptive statistics for return rate as shown in Table 1. The value of Kurtosis is larger than 10, therefore the distribution of data for return rate follows non-normal distribution. This finding was confirmed by using Jarque -Bera test that indicates 2501.116 that is deviated from normal distribution. The probability value also indicates 0.0000 which indicates data follows non-normal distribution.

Table 1: Descriptive statistics for a return rate

Parameter	Value
Mean	-0.161951
Maximum	26.82640
Minimum	-24.01411
Std. Dev.	4.133950
Skewness	0.711537
Kurtosis	12.98575
Jarque-Bera statistic	2501.116
Probability	0.000000
Distribution	Non-normal

Then, this study performed a unit root test for return rate of share price. Table 2 shows the unit root test using ADF, PP and KPS. The result shows all three types of unit root test indicate the stationarity data.

Table 2: Unit root test

Variable	ADF	PP	KPSS
Level (intercept)	-25.09492	-25.08907	0.147702
Probability	0.0000	0.0000	0.463000
Comment	Stationary	Stationary	Stationary
Level (Trend and intercept)	-25.10319	-25.09504	0.103324
Probability	0.0000	0.0000	0.146000
Comment	Stationary	Stationary	Stationary

Next, this study performed an estimation of the model for volatility. This study selected ARMA (2,2) as mean equation, based on Akaike info criterion (AIC), Schwarz criterion (SC), and Hannan-Quinn criteria (HQC). As comparing to other models, ARMA (2,2) shows minimum value for AIC, SC and HQC. ARMA is a model of autoregression (AR) analysis and moving average (MA) are both applied to time-series data that is well behaved. In ARMA it is assumed that the time series is stationary and when it fluctuates, it does so uniformly around a particular time.

After that, this study using GARCH (1,1), GARCH (1,1)-M, EGARCH (1,1) and TGARCH (1,1). Generalized Autoregressive Conditional Heteroskedasticity (GARCH) is a statistical model used in analyzing time-series data where the variance error is believed to be serially autocorrelated. GARCH models assume that the variance of the error term follows an autoregressive moving average process. Table 3 shows the estimation of volatility models. AIC, SC, and HQN's values show the fittest model is TGARCH (1,1). The model was estimated using the maximum likelihood procedure assuming normally distributed errors.

This study also performed an autocorrelation test using q-statistics that indicate TGARCH (1,1) is free from a serious autocorrelation problem. At the same time, Q-squared statistics that test heteroscedasticity indicate no heteroscedasticity characteristics. Next, the value t is 0.554343 with a probability of 0.0000. This value indicates the threshold effect is positive and significant. Therefore, the bad news is likely to be pronounced rather than good.

Table 3: Estimation of volatility model

Parameter	OLS	GARCH (1,1)	GARCH (1,1)-M	EGARCH (1,1)	TGARCH (1,1)
1. Mean Equation, ARMA (2,2)					
m	-0.086932	-0.083043	0.043510	-0.197020	-0.167375
Probability	0.6883	0.8255	0.9346	0.2141	0.3082
f_1	0.690510	0.897281	0.653907	1.115171	0.654370
Probability	0.0014	0.0638	0.0246	0.0000	0.0028
f_2	-0.358788	-0.688490	-0.570018	-0.796779	-0.589006
Probability	0.1447	0.0122	0.0139	0.0000	0.0011
q_1	-0.735021	-0.932782	-0.623629	-1.151395	-0.638927
Probability	0.0006	0.0449	0.0267	0.0000	0.0020
q_2	0.463735	0.734825	0.590730	0.855820	0.621037
Probability	0.0437	0.0054	0.0074	0.0000	0.0003
l			-0.002349		
Probability			0.9884		
2. Model selection					
Akaike info criterion (AIC)	5.727161	5.81133	5.546196	5.530372	5.5121212
Schwarz criterion (SC)	5.774509	5.874464	5.617219	5.601394	5.583143
Hannan-Quinn criteria (HQC)	5.745671	5.836014	5.573962	5.558137	5.539886
3. Variance Equation					
w		11.55443	3.611872	0.212820	3.318744
Probability		0.0802	0.0000	0.0131	0.0000
a_1		0.127024	0.520664		0.243791
Probability		0.1377	0.0000		0.0000
b_1		0.577024	0.423349		0.451191
Probability		0.0174	0.0000		0.0000
a				0.586838	
Probability				0.0000	
g				-0.196684	
Probability				0.0000	
b				0.771562	
Probability				0.0000	
t					0.554343

Probability					0.0000
4. Diagnostics					
Q-statistics (36 lags)	35.256	35.424	41.663	36.698	0.41084
Probability	0.317	0.310	0.118	0.260	0.130
Comment on the existence of autocorrelation problem	No	No	No	No	No
Q-squared statistics (36 lags)	89.687	40.124	31.478	34.546	33.855
Probability	0.000	0.292	0.684	0.538	0.571
Comment on the existence of heteroscedasticity problem	Yes	No	No	No	No
5. Decision for suitability of model selection	No	No	No	No	Yes

5. Conclusion

The main objective of this study is to evaluate volatility using appropriate model in econometrics. This company selected one airlines company that listed on Malaysia Stock Exchange. Main finding of this study is described as follows:

1. The selection of data starts from February 2020 until June 2022. The number of daily observations is 545 days. The value of the share price on the first-day observation is MYR 1.16. Due to the COVID-19 outbreak, the share price keeps decreasing until reached MYR 0.705 on the last observation.
2. During COVID-19 outbreak, result shows there is volatility clustering.
3. Data distribution for return rate confirmed using Jarque-Bera test. The Jarque -Bera statistics value is 2501.116 that indicates return rate data deviated from a normal distribution. The probability value also indicates 0.0000 which indicates data follows the non-normal distribution.
4. The unit root test was performed using ADF, PP and KPS. The result shows all three types of unit root tests indicate the stationarity data.
5. TGARCH (1,1) is the best-fitted model based on AIC, SC, and HQC. Next, the value is 0.554343 a with a probability of 0.0000. This value indicates the threshold effect is positive and significant. Therefore, the bad news is likely to be pronounced rather than good.

Acknowledgments

This study was supported by a research grant from Universiti Utara Malaysia (UUM), S/O Code: 14249, Development and Ecosystem Research Grant Scheme. We thank you for the facilities provided by Universiti Utara Malaysia (UUM) and Universiti Malaysia Perlis (UniMAP).

References

- Abu Bakar, N. and Rosbi, S. (2022). Modeling Volatility for High-Frequency Data of Cryptocurrency Bitcoin Price using Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model. International Journal of Advanced Engineering Research and Science (IJAERS), 9(9), 573-579. [CrossRef](#)
- Abu Bakar, N. and Rosbi, S. (2022). Effect of Coronavirus Disease (COVID-19) to Airlines Industry. IOSR Journal of Economics and Finance, 13(2), 35-44.
- Abu Bakar, N., Rosbi, S. and Uzaki, K. (2022). Impact of Coronavirus Disease (COVID-19) towards Hotel Tourism Industry. International Journal of Advanced Engineering Research and Science, 9(3), 43-50.

- Abu Bakar, N. and Rosbi, S. (2021a). Effect of COVID-19 outbreak towards banking and finance industry. *International Journal of Advanced Engineering, Management and Science*, 7(3), 1-5. [CrossRef](#)
- Abu Bakar, N. and Rosbi, S. (2021b). Impact of Coronavirus Disease (COVID-19) towards Economy and Vaccine Industry. *International Journal of Advanced Engineering Research and Science*, 8(2), 68-72.
- Abu Bakar, N., Rosbi, S. and Uzaki, K. (2020). Weighted Moving Average Method for Forecasting of Cryptocurrency Price: A Data Analytical Study on XRP Ripple Cryptocurrency. *International Journal of Advances in Scientific Research and Engineering*, 6(1), 127-133. [CrossRef](#)
- Abu Bakar, N. and Rosbi, S. (2020a). Effectiveness of lockdown policy to control spreading of Coronavirus disease 2019 (COVID-19). *IOSR Journal of Business and Management*, 22(8), 34-41.
- Abu Bakar, N. and Rosbi, S. (2020b). Impact of Coronavirus Disease 2019 (COVID-19) to Equity Market and Currency Exchange Rate. *IOSR Journal of Economics and Finance*, 11(2), 17-26.
- Abu Bakar, N., Rosbi, S. and Uzaki, K. (2019). Forecasting cryptocurrency price movement using moving average method: a case study of bitcoin cash. *International Journal of Advanced Research*, 7(12), 609-614.
- Abu Bakar, N., Rosbi, S. and Uzaki, K. (2017). Cryptocurrency Framework Diagnostics from Islamic Finance Perspective: A New Insight of Bitcoin System Transaction. *International Journal of Management Science and Business Administration*, 4(1), 19-28. [CrossRef](#)
- Benlagha, N. and Hemrit, W. (2022). Asymmetric determinants of Bitcoin's wild price movements. *Managerial Finance*, 1-21. [CrossRef](#)
- Diniz, R., Prince, D.d. and Maciel, L. (2022). Bubble detection in Bitcoin and Ethereum and its relationship with volatility regimes. *Journal of Economic Studies*, 1-19. [CrossRef](#)
- Dubey, P. (2022). Short-run and long-run determinants of bitcoin returns: transnational evidence. *Review of Behavioral Finance*, 14(4), 533-544. [CrossRef](#)
- Grira, J., Guizani, S. and Kahloul, I. (2022). Bitcoin's hedging attributes against equity market volatility: empirical evidence during the COVID-19 pandemic. *Journal of Risk Finance*, 1-14. [CrossRef](#)
- Hung, N.T. (2022). Asymmetric connectedness among S&P 500, crude oil, gold and Bitcoin. *Managerial Finance*, 48(4), 587-610. [CrossRef](#)
- Kakinuma, Y. (2022). Nexus between Southeast Asian stock markets, bitcoin and gold: spillover effect before and during the COVID-19 pandemic. *Journal of Asia Business Studies*, 16(4), 693-711. [CrossRef](#)
- Kamran, M., Butt, P., Abdel-Razzaq, A. and Djajadikerta, H.G. (2022). Is Bitcoin a safe haven? Application of FinTech to safeguard Australian stock markets. *Studies in Economics and Finance*, 39(3), 386-402.
- Kumar, S., Kumar, A. and Singh, G. (2022). Gold, crude oil, bitcoin and Indian stock market: recent confirmation from nonlinear ARDL analysis. *Journal of Economic Studies*, 1-18. [CrossRef](#)
- Lee, Y. and Rhee, J.H. (2022). A VECM analysis of Bitcoin price using time-varying cointegration approach. *Journal of Derivatives and Quantitative Studies*, 30(3), 197-218. [CrossRef](#)