Determining the Appropriate Time Series Model for the Malaysia Stock Price during Continuous Pandemic Waves: Case of COVID-19

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Abstract
As the series of COVID-19 outbreaks was reported and the declaration of this disease as pandemic, the global financial market, including Malaysia has affected. The uncertainty of this pandemic has led to larger volatility and an appropriate time series model are required to guarantee that the market players made a wise investment decision. Therefore, this study aims to investigate the movement of FTSE Bursa Malaysia stock indices and determine the appropriate model for the sample period. We included the daily data from January 2020 to August 2021 to overview the stock market volatility and Autoregressive Integrated Moving Average (ARIMA) was applied to determine a reliable model. The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models then was fitting in when the presence of heteroscedasticity in the data set was discovered. The result has shown that ARIMA (1,2,1) – GARCH (1,1) is the fitted model and the volatility was well-determined during the pandemic. In addition, the existence of leverage effect was confirmed using Exponential GARCH (EGARCH) and a positive risk premium was detected using Symmetric Mean GARCH (GARCH-M). Finally, it is recommended for researchers to use an extended sample period to see the behaviour of the stock market when Malaysia vaccination program has completed.
Keywords: Volatility, ARIMA-GARCH, COVID-19, Pandemic, Stock Market

Introduction

The Coronavirus (COVID-19) outbreak was later announced as a pandemic has negatively hit the financial market as most countries started implementing the movement restriction and closure of business activities (Toda, 2020). Baldwin and Mauro (2020) stated that the economic system was undergoing a few blows, which are the reduction in household spending, disruption in the import and export activities, and lastly, the "wait-and-see" approach will affect the manufacturing sector. Meanwhile, Ozili (2020) highlighted that the COVID-19 pandemic had disrupted the stock market by shutting down the business and corporate activities. Besides, the study also mentioned that the uncertainty of this pandemic has led to larger volatility in the stock market, and it influenced the investors' investment decisions in the stock market.

When China decided to implement a lockdown to control the widespread of the disease, this has affected the supply and demand throughout the world and negatively impacted Malaysia's economic system. In addition, the pandemic has significantly impacted Malaysia's financial markets, especially with the implementation of travel restrictions, social distancing, lockdowns and massive unemployment that have struck economies for almost two years. In Malaysia, the first COVID-19 cases were recorded on 25 January 2020 and increased dramatically to 2626 cases in 2 months. Due to the outbreak, the government of Malaysia has announced a series of movement control orders (MCO) from March 2020 till the present. That had increased the volatility of the stock market; thus, modelling them is essential. Shehzad et al. (2020) show that the Asian market was less affected by COVID-19 than the European market.

In contrast, Zeren and Hizarci (2020) found a cointegration relationship in the stock markets in China, Korea, and Spain. However, they observed no connection between the COVID cases and the performance of the stock markets in France, Germany, and Italy, hence signalling that these stock markets were not affected by the spread of COVID-19. In the context of the Malaysian market, Lee et.al (2020) found that the numbers of COVID-19 cases tended to adversely affect the performance of the KLCI index and all sectoral indices, except for the Real Estate Investment Fund (REIT) index.

Previously, many researchers used the ARIMA-GARCH model in modelling the stock market during financial crises (Shamiri and Isa, 2009; Ahmed and Suliman, 2011; Islam, 2013). The Autoregressive Integrated Moving Average (ARIMA) are simplistic linear models but cannot find complex, subtle patterns in the time-series data; meanwhile, the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) is a model that is widely used in measuring the volatility of high-frequency financial data like daily stock or stock index returns. Chaudhary et al (2020) analysed the stock market indices of the top 10 countries based on GDP using the standard GARCH model. That result found that the pandemic has increased the volatility of these indices. Shehzad et al (2020) also applied the Asymmetric Power GARCH model with dummy variables to investigate the impact of the Global Financial Crisis and COVID-19 on some of the stock markets indices such as S&P 500 (US), Nasdaq Composite Index (US), DAX 30 (Germany), FTSE MIB (Italy), Nikkei 225 Index (Japan), and SSEC (China).

In addition, a study by Chuan et. al (2021) found that EGARCH can detect the leverage effect when stock market returns are negatively correlated to its volatility. They also documented

that standard GARCH(1,1), GARCH-M(1,1), and EGARCH(1,1) models are suitable to predict volatility for both Malaysia and Singapore stock market returns. This result aligned with Mohd Nor & Shamiri (2007) research that discovered the asymmetric models, such as EGARCH and GJR-GARCH, outperform the symmetric GARCH model in the Malaysian and Singaporean stock markets. Goudarzi and Ramanarayanan (2011) also used asymmetric models of EGARCH and TGARCH to study the effects of good news and bad news on volatility in the Indian stock market. In addition, Alagidede and Panagiotidis (2009) also used GARCH models to examine the relationship between volatility and risk premium on the largest 7-African stock markets.

The stock market is an essential part of the capital market. Estimating financial time series such as stock returns is vital for investors, financial analysts, and policymakers. As Abdalla & Suliman (2012) mentioned, the time series model guarantees that the market players made a wise investment decision. Besides that, data from the time series of the stock market also plays an essential role in the financial market as the information gained from the analysis would determine the profits earned. For that reason, the volatility of the stock market is considered a widespread measure of risk for investors and modelling the volatility became crucial to ensure the investor does not miss a good investment opportunity. Accordingly, volatility plays a vital role in the financial market, but it is not directly observable, varies over time and is highly sensitive to financial market changes (Awalludin et. al., 2018). One of the significant drawbacks of the previous study, none of them has included all four waves of the outbreak in Malaysia, especially the recent two waves that hit the healthcare system. Therefore, like Lee et. al (2020) recommended, this paper analysed a more extended sample period that considered all the waves that had hit Malaysia so far and developed a fitted and reliable ARIMA-GARCH model to find out what is happening in Malaysia stock market.

Data and Methodology
This paper considers the four waves of the outbreak in Malaysia and uses FTSE Bursa Malaysia stock price from January 2020 until August 2021. We downloaded the daily time series from Yahoo Finance as per a study by Omar and Halim (2015) and Chuan et. al (2021). Then, the daily return was calculated using the natural log difference approach (Duttilo et. al, 2021). Besides, to emphasize the COVID-19 pandemic outbreaks, the considered period does not include the financial crises (1997 and 2008) and the political issues in 2019.
The investigation was performed using the five-step procedures: data collection, trend analysis, differencing, model identification, and model evaluation. The models used in this study was concisely chosen based on past researches. The reliability of these models in capturing the dynamic characteristics of stock index returns was successfully demonstrated by many researchers (Gherghina et al., 2021; Duttilo et al., 2021). Floros (2008) also models the volatility of middle-east stock indices using GARCH-type models over the two financial crises, the Asian Financial Crisis and Global Financial Crisis, and concluded that the GARCH models are proficient in capturing the dynamics of stock returns like volatility clustering and leverage effects.

Autoregressive Moving-Average (ARMA)
Box and Jenkins has designed the ARMA model as a random time-sequence model. This model consist of three basic types of ARMA model, which are Autoregressive (AR) model, Moving Average (MA) model, and the Autoregressive Moving Average (ARMA). The equation of the ARMA model is written below.

$$Y_t - \varphi_1 Y_{t-1} - ... - \varphi_p Y_{t-p} = \alpha_t - \theta_1 \alpha_{t-1} - ... - \theta_q \alpha_{t-q}$$

Generalized Autoregressive Conditional Heteroscedasticity (GARCH)

A general observation about the unexpected component of asset returns is that large shocks tend to be followed by more significant shocks, and small shocks tend to be followed by more small changes in either direction. In other words, the volatility of asset returns appears to be serially correlated. The econometric term describes this feature as the autoregressive conditional heteroscedasticity (ARCH), which states that the time-series variance depends on their past realizations. The standard ARCH model was introduced by Engle (1982) and generalized (GARCH) by Engle and Bollerslev (1986). In his model, Engle defines conditional variance as a deterministic function of lagged squared residuals. In the ARCH (p) model, the conditional variance is given by:

$$\sigma_t^2 = \omega + \alpha \in_{t-1}^2$$

Where ω and α non-negative constants (in order for σ_t^2 to be non-negative).

The equation above gives the ARCH model formulation to depict volatility as the clustering of large shocks to the dependent variable. This formula then was extended by Bollerslev and introducing lagged conditional variances in the conditional variance equation. The GARCH model is commonly used in its most simple form, where the simplest GARCH (1,1) specification is:

$$\sigma_t^2 = \omega + \alpha \in_{t-1}^2 + \beta \sigma_{t-1}^2$$

Where ω is a constant

$\in_{t-1}^2$ is the ARCH term

σ_{t-1}^2 is the GARCH term

Higher-order GARCH models denoted GARCH (q,p) can be estimated by choosing either q or p greater than 1. The representation of the GARCH (q,p) variance is:

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{p} \alpha_i \in_{t-1}^2$$

Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH)

EGARCH is used to model excess conditional kurtosis in stock return indices based on a generalized exponential distribution (Nelson, 1991). The extension by Nelson consider that the down movements are more significant in estimating the volatility. Therefore, the specification for the conditional variance of the EGARCH model is as following:

$$\log(\sigma_t^2) = \omega + \sum_{j=1}^{q} \beta_j \log(\sigma_{t-j}^2) + \sum_{i=1}^{p} \alpha_i \left| \frac{\in_{t-i}}{\sigma_{t-i}} \right| + \sum_{k=1}^{r} \gamma_k \frac{\in_{t-k}}{\sigma_{t-k}}$$

The left-hand side is the *log* of the conditional variance. This implies that the leverage effect is exponential rather than quadratic and that forecasts of the conditional variance are guaranteed to be nonnegative. The presence of leverage effects can be tested by the hypothesis that $\gamma_i < 0$. The impact is asymmetric if $\gamma_i \neq 0$.

Symmetric Mean Generalized Autoregressive Conditional Heteroscedasticity (GARCH-M)
Engle et al. (1987) developed the symmetric mean GARCH (GARCH-M) model in the following equations:

$$\gamma_t = c + \lambda \sigma_t^2 + u_t$$
$$\sigma_t^2 = \alpha + \theta_1 \sigma_{t-1}^2 + b_1 u_{t-1}^2$$

The mean equation includes the variance $\left(\sigma_t^2\right)$ because the variance serves as a proxy for risk. Investors are risk-averse, and the parameter λ reflects the risk premium. Consequently, investors are willing to increase their holdings in a risky asset if they earn a risk premium for doing so. The residual has the same relationship to the random noise or $\varepsilon_t = \sigma_t z_t$.

Results and Discussions
Trend Analysis
The graph in Figure 1 shows that the stock price presented several deterministic trends throughout the four waves of outbreak from the sample period of January 2020 till August 2021. The first outbreak started on 22 January 2020, has led to the decline of FTSE Bursa Malaysia stock price and later noted a dramatic drop after the second wave of the outbreak on 28 February 2020 (Hashim et al., 2021). The sharp decline was induced by the government's announcement of the first Movement Control Order (MCO) on 18 March 2020. For instance, Goudarzi and Ramanarayanan (2011) find that negative news has a more significant impact on volatility than positive news. After successfully lowering the number of Covid-19 cases between single- and double-digit, Malaysia hit the third wave of the outbreak in early October 2020 due to an election in one of the states in the country. The fourth epidemic wave hit Malaysia on June 2021, although Malaysia is still recovering from the third wave. This series of outbreaks has badly affected the country's healthcare system and caused a continuous drop in the stock price till August 2021. Therefore, by analysing the graph, the sample data is obviously non-stationary.
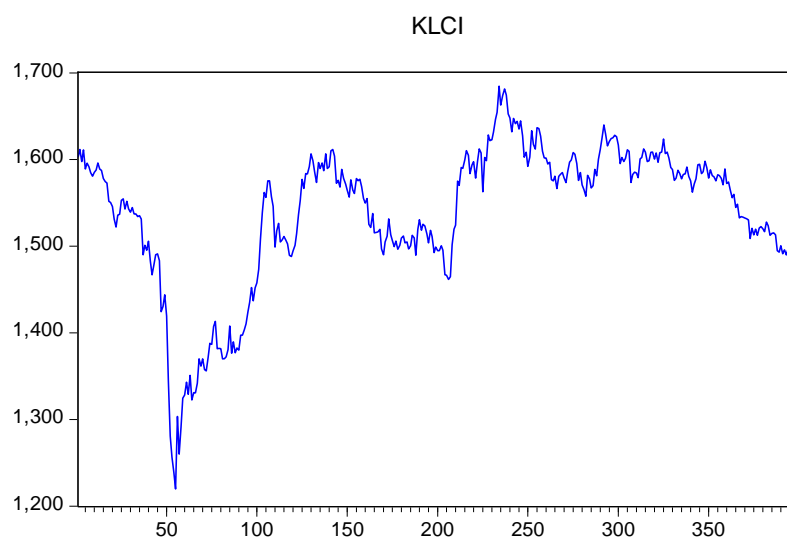
Figure 1: Time Series Plot for FTSE Bursa Malaysia KLCI from January 2020 till August 2021
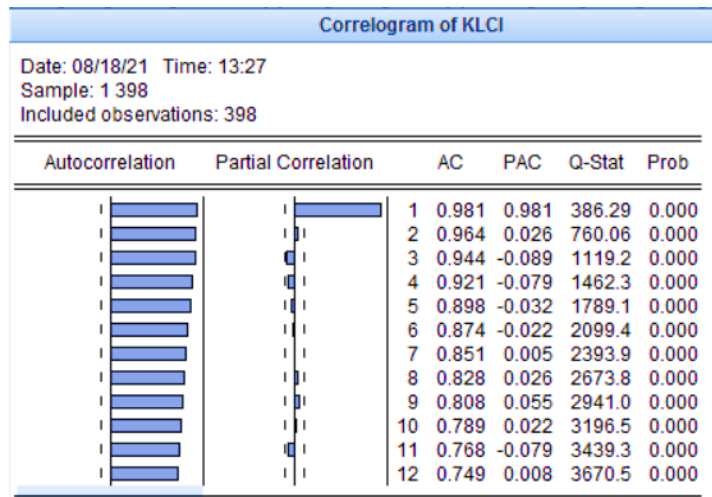
Figure 2: ACF and PACF of FTSE Bursa Malaysia KLCI

Referring to the movement displayed in the graph, Figure 2 shows that the ACF tails off extremely slowly over the lags. This result was supporting the early hypothesis that the data is non-stationary. Then, differencing was performed and we find that the stationary data only acquired after the second differencing.
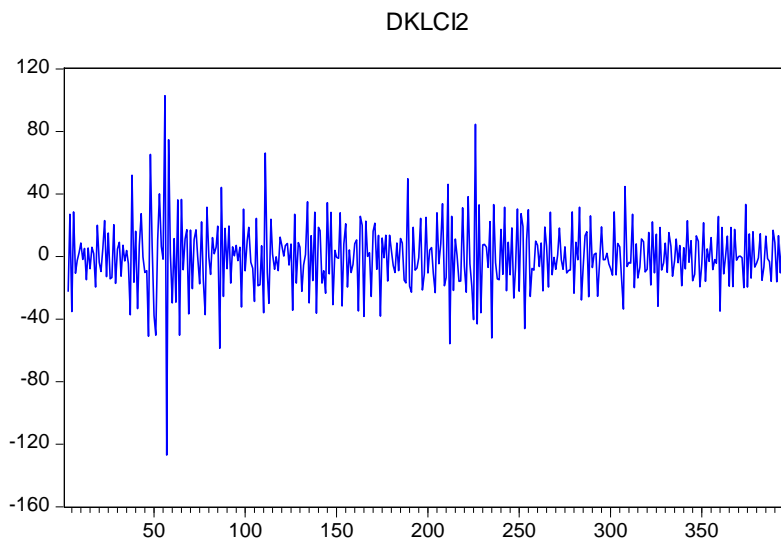

Figure 3: Time Series Plot of FTSE Bursa Malaysia KLCI after second differencing
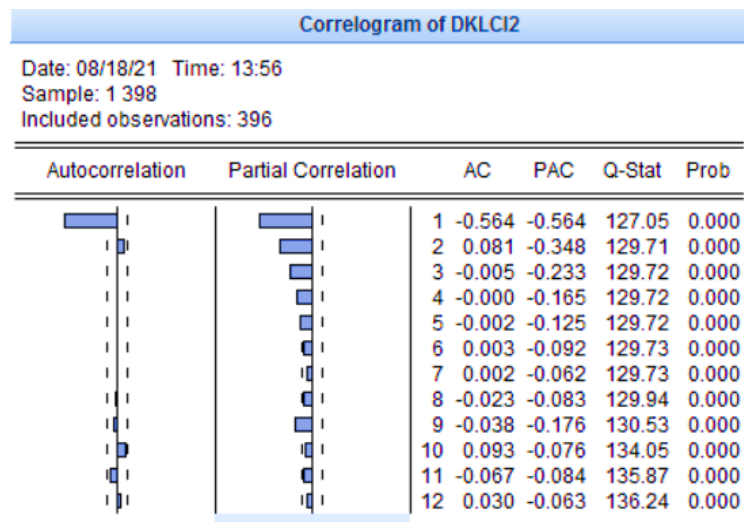
Figure 4: ACF and PACF of FTSE Bursa Malaysia KLCI after Second Differencing

From Figure 3, it shown that the stock price data fluctuated in different degree indicating that volatility changes over time, especially during the second and third waves of the outbreak when there is a remarkable high spike presented. An Islamic missionary and election caused these fluctuations, indicating that the data that include all four waves of outbreak is stationary in mean. Therefore, we assumed heteroscedasticity was exist in the sample period. This study also analyzes the ACF and PACF graphs as additional evidence before proceed with the heteroscedasticity test. Figure 4 clearly shows that there exist many significant values at the short lags. For that reason, ACF and PACF are not suitable in determining the fitted model to this sample data. Hence, this paper consider the theory of parsimony that focus on simplest model to ensure an accurate and reliable model can be derived.

Model Identification

By starting the model identification using the simplest model, we firstly generated and reported the output of models AR (1), MA (1) and ARMA (1, 1) in Table 1. The result presented that MA (1) coefficient was significant at a 5% significance level and fitted to the model. Additionally, the coefficient falls within -1 and 1, indicating that it fulfils the stationarity and invertibility conditions for the model. Besides that, MA (1) was considered as a better model since the value of R-square (0.519031) is higher than those in the AR (1) model (0.319297). This value indicate the reliability of this model in handling the variation of stock price compared to the later model. The Ljung-Box test also was done to verify the distribution of the residuals, whether it is independent or not. This independent residual shows that the main assumptions for the white noise was fulfil. The reported analysis shows that the white noise assumption was fulfilled at a few but not at the subsequent short lag. Thus, the MA (1) model does not satisfy the white noise assumption; hence a better model is needed. In addition, the patterns displayed by both ACF and PACF show significant values, supporting the fact that autocorrelation exists among the residuals. For that reason, a higher model is predicted to fit the stock price as there is a significant value around lag 3 for both ACF and PACF graphs. Deriving of a new ARMA model is then conducted to the MA (1) model to derived a more suitable model.

Table 1: Summary Table of the New Derived Models

Model	Coefficient	White Noise	AIC	SC
AR(1)	OK	NO	8.657805	8.667878
ARMA(1,1)	NO	NO	-	-
MA(1)	OK	OK	8.310539	8.320594
MA(2)	NO	NO	-	-
MA(3)	NO	NO	-	-
ARMA(2,1)	NO	NO	-	-
ARMA(1,2)	OK	OK	8.311159	8.341378
ARMA(2,2)	NO	NO	-	-
ARMA(1,3)	NO	NO	-	-

By reviewing the above table, we discovered that ARMA (1, 2) fits the data satisfactorily as the coefficient of AR and MA are significant and fulfilled the white noise assumptions. Thus, this statement was aligned with the previous assumption that a model with higher-order is required. Besides, the value of Akaike info Criterion (AIC) is lower in MA (1), making it a better model. Then, Overfitting is conducted again to get MA (3), ARMA (1, 3) and ARMA (2, 2) to verify the suitability of the predicted model. However, the result from Overfitting shows that all three models are not fitted for this sample period. After that, the ARCH-LM test is conducted to assess heteroscedasticity among the variance of the observed sample data. Based on the output in Table 2, it was evident that the null hypothesis is rejected due to the significant p-value at the 5% level, implying that heteroscedasticity exists within the data set. Hence, the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) shall be used to model volatility in the stock prices.

Table 2: ARCH-LM Test

Heteroskedasticity Test: ARCH			
F-statistic	9.531443	Prob. F(12,371)	0.0000
Obs*R-squared	90.48814	Prob. Chi-Square(12)	0.0000

Model Evaluation
As expected, the output of ARIMA (0, 2, 1) – GARCH (1, 1) presented that the coefficient is significant, hence accepting that ARIMA (0, 2, 1) is a reliable model. However, it was recommended to fit GARCH (1, 1) with a higher order model and find a fitted model. The result from the overfitting was presented in Table 3.

Table 3: Summary Table of the New Derived Models by Overfitting for ARIMA-GARCH

Model	Coefficient	White Noise	AIC	SC
MA(1)	OK	NO	8.163253	8.203469
MA(2)	NO	NO	-	-
ARMA(1,1)	OK	OK	8.149151	8.199517
ARMA(2,1)	NO	-	-	-
ARMA(1,2)	OK	NO	-	-
ARMA (2,2)	NO	-	-	-
ARMA(1,3)	OK	OK	8.174635	8.245146

After conducting several overfitting, the final model obtained was ARIMA (1,2,1)– GARCH (1,1). It was showing that both ARMA (1,1) and ARMA (1,3) are significant, but using the value of AIC in comparison, it was supported that ARMA (1,1) is a better model since it has lower value of AIC. The output of the constructed model is as shown in Table 4.

Table 4: ARIMA (1,2,1) – GARCH (1,1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
AR(1)	-0.116328	0.057792	-2.012886	0.0441
MA(1)	-0.998854	0.001530	-652.9998	0.0000
Variance Equation				
C	9.168433	4.719203	1.942793	0.0520
RESID(-1)^2	0.093224	0.022470	4.148753	0.0000
GARCH(-1)	0.866427	0.041342	20.95771	0.0000
R-squared	0.516312	Mean dependent var		0.028886
Adjusted R-squared	0.515081	S.D. dependent var		22.22048
S.E. of regression	15.47349	Akaike info criterion		8.149151
Sum squared resid	94095.52	Schwarz criterion		8.199517
Log likelihood	-1604.457	Hannan-Quinn criter.		8.169106
Durbin-Watson stat	1.819183			

Referring to the reported output, it shows that both coefficient are significant at 5% level and fulfill the stationarity and invertibility conditions respectively. Because of that, the GARCH (1,1) model are suitable in modelling the time-varying conditional variance that exist in the data set.

Table 5: ARIMA (0,2,1) – EGARCH (1,1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
MA(1)	-0.998879	0.001200	-832.3981	0.0000
Variance Equation				
C(2)	0.062630	0.119280	0.525068	0.5995
C(3)	0.192959	0.041378	4.663333	0.0000
C(4)	-0.047091	0.021278	-2.213085	0.0269
C(5)	0.960993	0.026741	35.93660	0.0000
R-squared	0.517980	Mean dependent var	-0.028005
Adjusted R-squared	0.517980	S.D. dependent var	22.22120
S.E. of regression	15.42766	Akaike info criterion	8.169210
Sum squared resid	94015.07	Schwarz criterion	8.219480
Log likelihood	-1612.504	Hannan-Quinn criter.	8.189125
Durbin-Watson stat	2.071543		

Table 6: ARIMA (0,2,1) – GARCH-M (1,1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	2.21E-05	0.000254	0.087076	0.9306
MA(1)	-0.998357	0.001545	-646.3211	0.0000
Variance Equation				
C	9.137047	5.070829	1.801884	0.0716
RESID(-1)^2	0.090570	0.023532	3.848777	0.0001
GARCH(-1)	0.868903	0.043710	19.87881	0.0000
R-squared	0.518619	Mean dependent var		-0.028005
Adjusted R-squared	0.517397	S.D. dependent var		22.22120
S.E. of regression	15.43698	Akaike info criterion		8.159428
Sum squared resid	93890.30	Schwarz criterion		8.209699
Log likelihood	-1610.567	Hannan-Quinn criter.		8.179344
Durbin-Watson stat	2.075378			

Then, the model is fitted with an EGARCH and GARCH-M, and after conducted overfit and underfit, the study finds that MA(1) is the best model for both of them. Therefore, ARIMA (0,2,1) – EGARCH (1,1) and ARIMA (0,2,1) – GARCH-M (1,1) are the fitted model for EGARCH and GARCH-M. EGARCH was used to identify the leverage effect among the stock prices during the waves of COVID-19 outbreak. In contrast, GARCH-M is used to investigate the proposition under Capital Asset Pricing Model (CAPM). From the output shown in Table 5, C (4) coefficient is negative and significant under a 5% significant level. This result suggested that the bad news will give a big blow to the fluctuations of the stock prices compared to the good news (Goudarzi and Ramanarayanan, 2011). It was proven by the presence of downward trend for the past two years and the unconsistent functuations in the initial analysis presented in Figure 1. Instead of that, the result of GARCH-M indicate the risk premium is not significant to hedge against holding a risky asset. Or the asset in question may not be risky to hold.

Conclusions and Recommendations
The risk is usually uncertain for the investor, and the huge up and downshifts in both developed and emerging markets are regular in the financial market. Financial crises over the years are a known factor that affects the fluctuations in the stock market. In fighting the spread of COVID-19 for the past two years, the Malaysian stock market has faced an enormous challenge in keeping its volatility. Star Media (2020) reported major shareholders of listed companies has disposed of their shares in the first few trading days of MCO due to the uncertainty caused by the COVID-19 and MCO. Therefore, this research implemented the ARIMA-GARCH model for a daily data set from January 2020 till August 2021 to study stock price movement during four waves of COVID-19 in Malaysia.

This paper finds a deterministic trend in the stock price as the country is fighting with the pandemic. Closure of business activity, movement control order, and struggling to control the widespread disease have led to a dramatic drop in the stock price, as reported by Lee et.al (2020). The analysis on the daily data set showed heteroscedasticity, which led to the use of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) following Alagidede and Panagiotidis (2009). When analyzing the sample period, it also reported that the reliability of the model was change when fitted into GARCH family models. Overfit and underfit were

conducted to find the best-fitted model for the GARCH, EGARCH and GARCH-M. Finally, we found that ARIMA (1,2,1)– GARCH (1,1) is the best model for this data set. Besides, the result also shows that the continuous waves of the COVID-19 outbreak have affected the stock market volatility, and the risk premium was positive, indicating the asset maybe not be risky to hold (Chuan et. al, 2021).

This study contributes to the research literature on how the COVID-19 pandemic has affected stock markets' volatility. It shows that the pandemic has changed the characteristics of the GARCH process and its underlying distribution. For further research, it is recommended for researchers to use a more extended sample period to see the behaviour of the stock market after the Malaysia vaccination program has reached herd immunity. In addition, the pre and post-pandemic situation also can be evaluated in the future.

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