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# THE IMPACT OF COVID-19 OUTBREAKS ON THE VOLATILITY OF THE STOCK MARKET IN MALAYSIA

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**ABSTRACT**

*At the end of 2019, a serious disease that has existed in Wuhan, China, and has been identified as Coronavirus disease (COVID-19), and it has become a pandemic as it has spread furiously all over the world. To prevent the spread of the disease, all countries declared lockdown, and all activities in the country were required to halt immediately, resulting in economic turmoil. The stock market has become volatile and has been exhibiting a downtrend as returns have decreased. However, there is little attention given to investigating the stock market volatility in Malaysia, whereas volatility occurs in the market since the behaviour of the stock market moves up and down often during COVID-19. The objective of this study is to investigate the effect of COVID-19 on the volatility of the Kuala Lumpur Composite Index (KLCI) and 13 sectoral indices; KL Construction (KLCT), KL Consumer Products (KLCM), KL Energy (KLEN), KL Finance (KLFI), KL Healthcare (KLHC), KL Industrial Products (KLIP), KL Plantation (KLPL), KL Property (KLPR), KL REIT (KLRE), KL Technology (KLTE), KL Telecommunications and Media (KLTC), KL Transportation and Logistics (KLTP) and KL Utilities (KLUT) as well as to find out which sectors are affected by this outbreak compared to the KLCI. The duration of the data taken is from 1 October 2018, until 30 September 2021. The method that is used to analyze the volatility is the Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) model. The results show that there is a significant effect of COVID-19 on the return of the stock market. Most of the results are similar for the sectoral indices in the presence of the AutoRegressive Conditional Heteroskedasticity (ARCH) effect. This study concludes that COVID-19 has had a significant negative impact on the KLCI and sectoral indices, whether in a positive or negative manner.*

**Keywords***: GARCH Model, KLCI, Sectoral Indices, Stock Market, Volatility*

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## 1. Introduction

Investment in the stock market involves risk but can be made safe with a minimum potential for long-term losses with accurate techniques and strategies. Stock market movement is related to volatility (Andersen *et al.*, 2003). Volatility occurs when the price of the stock market rises or falls drastically. In the financial market, it can be an important obstacle to attracting investment in the company. Past stock market performance is important for forecasting future stock market volatility, which is a significant input in investment decision-making and portfolio selection. A portfolio manager should know the likelihood of a future decrease in the portfolio. Historical data trends would be useful for stock market investors to strategize their asset allocation to maximize potential returns while limiting investor risk. Volatility can be utilized as a quantitative risk indicator, although volatility is not equal to risk. Volatility can be used for the predictability of risk. For the investor to measure and manage market risk more precisely, the volatility analysis of stock markets is essential and valuable for price assets, financial securities, and portfolio selection (Maqsood *et al.*, 2017). Portfolio managers and policymakers in emerging market economies can assess and protect themselves from risk using volatility metrics to determine their policies' typical benefits and costs. As the volatility of the stock market keeps increasing, the risk of investment keeps increasing as well (Sinakalai, 2011). The value of the stock price could be distributed over a wider range of values. This means that the stock price might move extremely in both directions over a short period of time. However, volatility appears to be not too bad because high volatility will provide a large return to the investors. The volatility of the stock market is mostly generated by uncertainty, which may be impacted by changes in tax rates, inflation rates and other monetary policy, but also by changes in the industry and by national and global events. According to Yong *et al.* (2021), the volatility of stock returns' nature will be shifted due to the financial crisis.

In the past years, a new global issue has erupted, which is called Coronavirus disease (COVID-19). This disease has given indemnities to our world since it was a pandemic that affected humans' health and caused a high mortality rate. The virus spreads rapidly among people through social interactions. This disease has urged the majority of economic sectors to close and stop production. This global pandemic has caused a rigid problem in people's daily lives, also as well as crumbling markets and economies (Goodell, 2020). The majority of countries all over the world have conducted lockdowns. As a consequence of that, the economic sectors had to stop for a while, which contributed to the financial crisis that happened in all the companies. According to the OECD (2020), COVID-19 has made the stock market globally accelerate its decline. Consequently, the entire world experienced a crash in the economy, resulting in a fall in stock prices below their normal rate. This current situation has led to market volatility because of the downtrend of the stock market. While the number of COVID-19 cases continues to rise alarmingly, it will have an impact on investor decisions as there is growing doubt and uncertainty among investors about whether they want to invest in our stock market or not. As stated by Ozili (2020b), uncertainty leads to higher volatility in the stock market as it affects investors' decisions. Additionally, investors also take into account the volatility and trend of the stock market when they are making investments.

The United States (US) showed a never-before-seen economic disruption and an unprecedented stock market decline when this pandemic came over (Hong *et al.*, 2021). This is because the investors sold their shares, which caused the supply to exceed the demand. Apart from this, Malaysia, as an emerging market country, has attracted many investors domestically and internationally. Since the global crisis has also impacted our country, investors might react and feel worried to keep investing in our stock market. However, from the past global epidemic, studies show that the stock market is immune to the epidemic. As COVID-19 occurred, we want to see the stock market in our country will still be immune or not. Previous studies showed that there are not many studies focused on Malaysia to investigate the volatility of the stock market during this pandemic. Some studies only investigated the stock market return without looking at its volatility and did not include the other economic sectors in Malaysia. As such, this study will investigate the effect of the COVID-19 outbreak on the volatility of the stock market in Malaysia and also make a comparison of which sectors get affected by COVID-19 outbreaks compared to the KLCI stock market.

## 2. Literature Review

### 2.1 The Impact of COVID-19 on the Stock Market

The COVID-19 pandemic had an impact on the stock market movement. Ngwakwe (2020) conducted a study in several nations, including China, Europe, and the United States (US), to investigate the various implications of stock market performance in these countries during the epidemic. The Dow Jones Industrial Average Market Index and the Standard and Pore (S&P) (for the United States of America), the Shanghai Composite Index (for China), and the Euronext (for the European Union) were used in this study. The study analyzed data from the historical stock markets of these three nations in the 50 days leading up to the COVID-19 outbreak and throughout the first 50 days of the pandemic. According to the findings, the COVID-19 pandemic has had a significant impact on two market indexes, the Shanghai Composite Index and the Dow Jones Industrial Average. The Shanghai Composite Index showed resistance to the COVID-19 epidemic with a considerable increase in stock values within the first fifty days of the pandemic. The COVID-19 pandemic, on the other hand, affected the Dow Jones Industrial Average, and a significant drop in stock market value was observed during the first fifty days of the outbreak. The S&P 500 and the Euronext 100 indexes, on the other hand, showed no statistically significant difference in the mean stock price. Furthermore, during the first fifty days of the COVID-19 pandemic, all four stock market indexes experienced a higher degree of stock value fluctuation.

During the early stages of the outbreak, COVID-19 showed a negative side on the stock markets of China and other Asian nations and also had a limited impact, according to a study done by He *et al.* (2020). The goal of the study is to investigate the COVID-19 impact on stock markets as well as its spillover effects. The daily return data from stock markets in the People's Republic of China, Italy, South Korea, France, Spain, Germany, Japan, and the United States of America were analyzed using conventional t-tests and non-parametric Mann–Whitney tests. The results of the study revealed that COVID-19 has a negative but relatively brief influence on stock markets in the countries involved. The impact of COVID-19 on stock markets has a reciprocal spillover effect among Asian, European, and American countries.

Liu *et al.* (2020) investigated the impact of the coronavirus outbreak on 21 prominent stock market indexes in major affected nations such as Japan, Korea, Singapore, the United States, Germany, Italy, and the United Kingdom is assessed in this article. Following the disease outbreaks, financial markets in affected countries were plummeting. In comparison to other countries, Asian countries had greater negative abnormal returns.

In Malaysia, several studies measured the impact of COVID-19 towards KLCI index performance in Malaysia. A study by Lee *et al.* (2020) found that the performance of the KLCI index and all sectoral indexes, with the exception of the Real Estate Investment Fund (REIT) index, tended to deteriorate from higher COVID-19 cases in Malaysia. Same results were found in Mehmood *et al.* (2021) and revealed that energy, real estate, and finance had the worst performance indexes, but healthcare, technology, telecommunications, and media had the least impact.

### 2.2 Stock Market Performance and Volatility

The macroeconomic factors are known to affect the stock market performance. This can be seen in the study conducted by Badullahewage (2018), which examines the relationship between macroeconomic factors and stock market performance in Sri Lanka. The stock market performance was highly influenced by macroeconomics factors such as the inflation rate, exchange rate, interest rates, money supply, foreign direct investment, and many others. The study revealed that inflation and exchange rates have a greater impact on the stock market in

Sri Lanka than any other component. The study also stated that Sri Lanka's share market performance occasionally varies due to factor variation.

The global crisis also led to economic issues, whereas it represents a steady and significant downfall in all economic indexes over a relatively short period, leading particularly to the failure of the financial markets. As stated in Onuoha & Nwaiwu (2016), Nigeria's stock market showed a considerable influence on the global financial crisis. They also mentioned that stock markets are sensitive and react swiftly to national and worldwide developments.

Chin *et al.* (2018) studied the sectorial performance of KLSE Bursa Malaysia. The data of the study ranged from 3 January 2007, to 30 December 2016, with a total of 2465 observations, and it includes the KLCI stock market indices. Eight sectors were chosen, which consisted of consumer product, plantation, finance, property, industrial product, trading service, construction and technology. The results demonstrated that the consumer products sector performed in all risk-adjusted-performance actions in the other sectors with higher profits and the top ranking. Moreover, compared to the stock market of KLCI, these sectoral indices are less volatile. This study also took into account the gold price, oil price, exchange rate and policy rate, but these factors showed little implication for stock return volatility.

As the investment is risky, it must be related to volatility. In Saad *et al.* (2017), market players focused primarily on the study of stock market volatility, as the majority of financial economy applications deal with volatility. The study investigated the volatility of several sectors in Malaysia using the stock market data from 867 companies and divided the main sectors into primary, secondary and tertiary. The findings revealed that there were five subsectors from these three sectors that had more than 60% volatility, while there were four subsectors that had volatility below 20%. Furthermore, the volatility values in various subsectors change significantly depending on the outcomes. This indicated the riskiness of each sub-individual sector's companies. The greater the risk, the higher the profit will be gained.

The study by Lazarul *et al.* (2020) investigated the volatility of the stock market in Malaysia, which implies seeing the endurance and effect of leverage in the stock market. The data was taken from FTSE BM KLCI, FTSE BM Top100, FTSE BM Mid70, and FTSE BM Small and covered weekly data stock prices from January 2000 to December 2018. It suggests that there is a continuing influence of the volatility shock on conditional variance in the stock market in Malaysia, as all the return series have volatility clustering. The negative impact on Malaysian stocks is greater than favourable news on volatility. It is said that Malaysia's stock market investors or traders respond more swiftly to bad news than positive news.

## 2.3 GARCH Model

Omar & Halim (2016) analyzed a study of market volatility in Malaysia using the Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) model. The sample includes 2473 observations from the FBM KLCI's daily index return from January 2002 to December 2011. They used three types of the GARCH model, which are GARCH (1,1), EGARCH and TGARCH. GARCH studies (1,1) demonstrated that volatility and persistent clustering affect stock market volatility. Furthermore, in the data set, asymmetric TGARCH and EGARCH models detect the presence of leverage effects. The latest analysis proves that the EGARCH model beats the other GARCH model classes and is best able to forecast volatility.

A study by Lim & Sek (2013) investigated the types of GARCH models that were used to calculate the volatility of the stock market in Malaysia when the Asian financial crisis occurred in 1997. The data was taken from 2 January 1990 to 30 December 2010 and was split into three categories which are pre-crisis, crisis and post-crisis. The findings showed that in the pre-crisis period, the symmetric GARCH model worked well, while in the crisis and post-crisis periods, the asymmetric GARCH models, which were EGARCH and TGARCH models, worked well to capture stock market volatility in Malaysia. This means that the GARCH model is the best indicator to measure the volatility of the stock market at various times.

The effectiveness of the GARCH model was also supported in the study by Lee *et al.* (2017) and Zakaria *et al.* (2020). The study in Lee *et al.* (2017) observed the three types of forecasting models, which were ARIMA, EWMA and GARCH (1,1). Four countries were selected, such as Malaysia and Indonesia, as emerging countries, while Japan and Hong Kong were recognized as developing countries. The results revealed that the GARCH (1,1) model is the best stock market forecast model in Malaysia, Indonesia and Japan, while the Hong Kong stock market provision is the best model for the EWMA model. For most stock markets in this sample, GARCH (1,1) seems to be the best provision model. In comparison to Malaysia, higher volatility in Hong Kong suggests that developed stock markets may have higher volatility than emerging markets. Zakaria *et al.* (2020) identified the general trend in KLCI stock return using two models, GARCH and ARIMA . Based on the results of this study, which were divided into an estimation part with 144 observations and an evaluation part with 60 observations for both models, it is evident that ARIMA is the best model for the evaluation part (1,1,1).

## 3. Data and Methodology

### 3.1 Data Collection

The data of the stock market are based on the daily closing price for Kuala Lumpur Composite Index (KLCI) and 13 sectoral indices and are collected from Investing.com. The period of data spanned from 1 October 2018 until 30 September 2021. This period is selected because the study covers the period before and during COVID-19. Hence, the sample is divided into three-sub periods, which are the full period (1 October 2018 - 30 September 2021), before COVID-19 (1 October 2018 - 29 November 2019) and during COVID-19 (2 December 2019 - 30 October 2021). The closing price of the stock market for KLCI and 13 sectoral indices are used to compute the stock return using the following formula:

$$r_t = ln\left(\frac{p_t}{p_{t-1}}\right)*100, \quad (1)$$

where

$r_t$ = daily return of KLCI

$p_t$ = the closing price of KLCI on day t

$p_{t-1}$ = the closing price of KLCI on the day before t

### 3.1 Methodology

Several analyses are conducted in this study. There are descriptive statistics, the unit root tests, the ARCH test and the GARCH model. All analyses are divided into three periods, which are: 1) the full period; 2) before COVID-19; and 3) during COVID-19. The periods are divided to compare the differences in the results among these three periods. The description of methodologies is discussed in the next section.

### 3.1.1 Descriptive statistics

The study computed descriptive statistics to illustrate the behaviour of the data. The measures are mean, median, standard deviation, skewness and kurtosis.

### 3.2.1 Unit Root Test - Augmented Dickey-Fuller (ADF) test

This study investigates the presence of unit roots in the data using the Augmented Dickey-Fuller (ADF) test. The test contains three levels which are level form, first difference and second difference.

The hypothesis testing for this test is shown below:

$H_0$: $\gamma = 0$ (Non-stationary and has unit root)

$H_1$: $\gamma < 0$ (Stationary and has no unit root)

If the test statistics reject the null hypothesis of the presence of unit root, it shows that the series is stationary. This will cause the data to be spurious and give an invalid result.

### 3.2.2 The GARCH Model

The ARCH test is conducted before proceeding to the GARCH model. If the ARCH effect is present, the GARCH model will be used to model the data (Bollerslev, 1986).

The mean equation for the series $y_t$, and the series is assumed to follow AR(1) model, and the equation for the variance is then assumed to be modeled by GARCH (1,1) and is given as follows:

$$h_t = \gamma_0 + \delta_1 h_{t-1} + \gamma_1 \mu_{t-1}^2, \tag{3}$$

where

$h_t$ = conditional variance

$\gamma_0$ = constant

$\delta_1$ = coefficient for $h_{t-1}$

$\gamma_1$ = coefficient for $\mu_{t-1}^2$

$h_{t-1}$ = conditional variance at lag 1

$\mu_{t-1}^2$ = squared residual at lag 1

The variance equation is denoted by $h_t$ which is the variance parameter at time *t* influenced by the past value of variance (lagged $h_t$) and past error term (lagged squared error term). Hence, for the general notation of GARCH (p,q), which introduces a new parameter of "p" refers to the number of lagged variance while "q" refers to the lagged squared error term.

The stability condition of the GARCH (1,1) model is such that: $0 < \delta_1 < 1$, $0 < \gamma_1 < 1$ and $\delta_1 + \gamma_1 < 1$. The Akaike information criterion(AIC), Schwarz Information criterion (SIC) and adjusted R-squared ($R^2$) values are taken into account while determining the GARCH model. The best GARCH model has the lowest AIC and SIC values and the greatest $R^2$ value.

For test-statistics:

All coefficients are compared to a 5% level of significance, and the p-value will measure the significance of the coefficients.

## 4. Results and Discussion

### 4.1 Descriptive Statistics Result

Tables 1 to 3 shows the result of descriptive statistics for the KLCI and sectoral indices for an overall period model, before and during the COVID-19 period. Before the COVID-19 period, as reported in Table 2, three sectoral indices that exhibited positive returns were KLCT, KLEN, and KLRE, indicating that they generated a profit for the entire period, whereas the other sectoral indices showed negative returns, indicating that they incurred losses. For Tables 1 and 3, the findings were quite similar except for KLTC during the COVID-19 period. The result in Table 3 reported that the standard deviation for all sectors were consistent in the stock return. Similar findings were obtained for kurtosis, where almost of them were large and exceeded 3, indicating that datasets have a leptokurtic distribution with heavy-tailed distribution. This signifies that almost sectors during the COVID-19 period exhibit negative skewness and more peaked curved.

Table 1. Descriptive Analysis for Variables in Full Period Model.

| | **Mean** | **Median** | **Standard Deviation** | **Kurtosis** | **Skewness** |
|---|---|---|---|---|---|
| Kuala Lumpur Composite Index (KLCI) | -0.0208 | -0.0184 | 0.8585 | 9.2401 | -0.1324 |
| KL Construction (KLCT) | -0.0254 | 0.0094 | 1.5882 | 12.5784 | -1.1571 |
| KL Consumer Product (KLCM) | -0.0237 | 0.0053 | 0.8096 | 9.1976 | -1.1016 |
| KL Energy (KLEN) | -0.0620 | -0.0743 | 2.3834 | 35.5335 | -2.1877 |
| KL Finance (KLFI) | -0.0211 | -0.0293 | 1.0586 | 17.9614 | 1.0986 |
| KL Healthcare (KLHC) | 0.0863 | -0.0381 | 1.7669 | 5.5504 | 0.6556 |
| KL Industrial Product (KLIP) | 0.0191 | 0.0312 | 1.2420 | 15.8759 | -1.4351 |
| KL Plantation (KLPL) | -0.0236 | -0.0562 | 0.9773 | 9.5524 | -0.1721 |
| KL Property (KLPR) | -0.0435 | -0.0634 | 1.0930 | 7.9655 | -0.7548 |
| KL REIT (KLRE) | -0.0209 | -0.0060 | 0.6593 | 22.4744 | -2.1037 |
| KL Technology (KLTE) | 0.1108 | 0.1684 | 1.8545 | 6.8611 | -0.7119 |
| KL Telecommunications & Media (KLTC) | -0.0082 | -2.2E-06 | 1.1489 | 4.6429 | 0.0047 |
| KL Transportation & Logistics (KLTP) | 0.0026 | 0.0322 | 1.1921 | 6.5849 | -0.4770 |
| KL Utilities (KLUT) | -0.0151 | -0.0330 | 0.8777 | 7.7015 | -0.5787 |

Table 2. Descriptive Analysis for Variables Before COVID-19 Period Model.

| | Mean | Median | Standard Deviation | Kurtosis | Skewness |
|---|---|---|---|---|---|
| Kuala Lumpur Composite Index (KLCI) | -0.0484 | -0.0598 | 0.5370 | 0.9322 | -0.2783 |
| KL Construction (KLCT) | 0.0084 | 0.0459 | 1.5002 | 12.2641 | -0.9219 |
| KL Consumer Product (KLCM) | -0.0410 | 0.0061 | 0.5600 | 3.9308 | -0.8960 |
| KL Energy (KLEN) | 0.0085 | 0.0802 | 1.3535 | 0.4354 | 0.0337 |
| KL Finance (KLFI) | -0.0516 | -0.0363 | 0.4925 | 2.1599 | 0.1174 |
| KL Healthcare (KLHC) | -0.0307 | -0.0336 | 0.7091 | 2.1223 | -0.0862 |
| KL Industrial Product (KLIP) | -0.0590 | -0.0196 | 0.6332 | 1.4992 | -0.3164 |
| KL Plantation (KLPL) | -0.0222 | -0.0644 | 0.7107 | 2.3215 | 0.2404 |
| KL Property (KLPR) | -0.0844 | -0.0744 | 0.7839 | 2.4833 | -0.1945 |
| KL REIT (KLRE) | 0.0146 | 0.0181 | 0.3988 | 1.7949 | 0.3223 |
| KL Technology (KLTE) | -0.0510 | 0.0321 | 1.4256 | 1.4427 | -0.1593 |
| KL Telecommunications & Media (KLTC) | -0.0239 | -0.0244 | 0.9323 | 2.3063 | 0.0377 |
| KL Transportation & Logistics (KLTP) | -0.0550 | -0.0420 | 0.7584 | 0.1495 | -0.0970 |
| KL Utilities (KLUT) | -0.0176 | -0.0461 | 0.7656 | 2.0265 | 0.0234 |

Table 3. Descriptive Analysis for Variables In During COVID-19 Period Model.

| | Mean | Median | Standard Deviation | Kurtosis | Skewness |
|---|---|---|---|---|---|
| Kuala Lumpur Composite Index (KLCI) | -0.0034 | 0.0081 | 1.0105 | 7.2682 | -0.1438 |
| KL Construction (KLCT) | -0.0467 | -0.0244 | 1.6425 | 12.6521 | -1.2623 |
| KL Consumer Product (KLCM) | -0.8960 | 0.0051 | 0.9337 | 7.7778 | -1.0751 |
| KL Energy (KLEN) | -0.1066 | -0.0949 | 2.8491 | 27.7314 | -2.0613 |
| KL Finance (KLFI) | -0.0018 | -0.0168 | 1.2943 | 12.2520 | 0.9403 |
| KL Healthcare (KLHC) | 0.1603 | -0.0498 | 2.1835 | 2.8979 | 0.4790 |
| KL Industrial Product (KLIP) | 0.0684 | 0.1156 | 1.5029 | 11.5157 | -1.3905 |
| KL Plantation (KLPL) | -0.0244 | -0.0499 | 1.1138 | 8.6413 | -0.2279 |
| KL Property (KLPR) | -0.0176 | -0.0148 | 1.2494 | 7.0558 | -0.8338 |
| KL REIT (KLRE) | -0.0434 | -0.0367 | 0.7799 | 17.8913 | -2.0423 |
| KL Technology (KLTE) | 0.2128 | 0.2405 | 2.0750 | 6.8282 | -0.8765 |
| KL Telecommunications & Media (KLTC) | 0.0017 | 0.0136 | 1.2677 | 4.4805 | -0.0145 |
| KL Transportation & Logistics (KLTP) | 0.0389 | 0.0702 | 1.3981 | 5.1837 | -0.5293 |
| KL Utilities (KLUT) | -0.0135 | -0.0258 | 0.9425 | 8.8344 | -0.7742 |

## 4.2 Unit Root Test - Augmented Dickey-Fuller (ADF) test Result

Table 4 represents the unit root test results for variables for all models at level form. For the full period model, the KLCI and all the sectoral indices show negative values of $\gamma$ and a p-value of zero. The null hypothesis of the existence of a unit root is rejected as $\gamma$ is smaller than 0, and the p-value obtained from the ADF test is less than 0.05. So, the variables in the full period model have no unit root and are stationary at level form. The results for the pre-COVID-19 period model and during the COVID-19 period model also illustrate that the KLCI and all sectoral indices have negative values of $\gamma$ and a p-value of zero, indicating that the null hypothesis has been rejected. It can be summarized that for the three-period models, the KLCI and sectoral indices are stationary in level form. As a result, the data are not erroneous and can be moved on to the next method. The data need to be in the stationary condition before modeling the data.

Table 4. Unit Root Test for Variables for All Models.

| | **t-statistics** | | | | | |
|---|---|---|---|---|---|---|
| | **Full period** | **p-value** | **Before COVID-19** | **p-value** | **During COVID-19** | **p-value** |
| Kuala Lumpur Composite Index (KLCI) | -27.9151 | 0.0000* | -16.1972 | 0.0000* | -22.0233 | 0.0000* |
| KL Construction (KLCT) | -24.4240 | 0.0000* | -16.1574 | 0.0000* | -18.4712 | 0.0000* |
| KL Consumer Product (KLCM) | -16.1676 | 0.0000* | -17.1687 | 0.0000* | -12.4442 | 0.0000* |
| KL Energy (KLEN) | -9.62789 | 0.0000* | -15.1042 | 0.0000* | -21.7485 | 0.0000* |
| KL Finance (KLFI) | -16.0166 | 0.0000* | -16.1271 | 0.0000* | -12.3129 | 0.0000* |
| KL Healthcare (KLHC) | -22.6756 | 0.0000* | -15.6901 | 0.0000* | -17.6385 | 0.0000* |
| KL Industrial Product (KLIP) | -12.9427 | 0.0000* | -17.1190 | 0.0000* | -21.0225 | 0.0000* |
| KL Plantation (KLPL) | -11.0493 | 0.0000* | -18.5772 | 0.0000* | -23.6839 | 0.0000* |
| KL Property (KLPR) | -14.2217 | 0.0000* | -14.4405 | 0.0000* | -10.7549 | 0.0000* |
| KL REIT (KLRE) | -15.0831 | 0.0000* | -19.3481 | 0.0000* | -11.1821 | 0.0000* |
| KL Technology (KLTE) | -16.3555 | 0.0000* | -14.7067 | 0.0000* | -12.9406 | 0.0000* |
| KL Telecommunications & Media (KLTC) | -16.9195 | 0.0000* | -15.5434 | 0.0000* | -13.3337 | 0.0000* |
| KL Transportation & Logistics (KLTP) | -26.3893 | 0.0000* | -16.3572 | 0.0000* | -20.6692 | 0.0000* |
| KL Utilities (KLUT) | -15.4770 | 0.0000* | -14.0841 | 0.0000* | -11.7994 | 0.0000* |

*The values are significant at the 5% level.

## 4.3 ARCH Test Result

Table 5 summarizes the ARCH test findings for the three-period models where the p-values are compared at a 5% significant level. The table displays the ARCH test results for all period models. The findings showed that before COVID-19, the majority of the sectors provided insignificant results of no ARCH effect except for KLCI, KLFI and KLRE. For the period during and full model, the ARCH effect is present (the heteroscedasticity in the variance of error) , indicating the need for GARCH modeling to estimate the parameter of the model. The result of no ARCH effect remains for all periods for KLEN, only indicating that this stock return for the sector did not affect by COVID-19.

Table 5. ARCH Test for Variables for All Models.

| | **F-statistics** | | | | | |
|---|---|---|---|---|---|---|
| | **Full period** | **p-value** | **Before COVID-19** | **p-value** | **During COVID-19** | **p-value** |
| Kuala Lumpur Composite Index (KLCI) | 90.9460 | 0.0000* | 8.6268 | 0.0036* | 52.1754 | 0.0000* |
| KL Construction (KLCT) | 55.0710 | 0.0000* | 0.0457 | 0.8309 | 84.2268 | 0.0000* |
| KL Consumer Product (KLCM) | 254.4619 | 0.0000* | 1.9154 | 0.1675 | 169.1571 | 0.0000* |
| KL Energy (KLEN) | 1.2207 | 0.2696 | 2.1083 | 0.1476 | 0.4163 | 0.5191 |
| KL Finance (KLFI) | 66.8876 | 0.0000* | 4.3782 | 0.0373* | 37.6288 | 0.0000* |
| KL Healthcare (KLHC) | 63.7238 | 0.0000* | 1.2745 | 0.2599 | 28.2057 | 0.0000* |
| KL Industrial Product (KLIP) | 42.6819 | 0.0000* | 0.2254 | 0.6353 | 23.2505 | 0.0000* |
| KL Plantation (KLPL) | 8.1316 | 0.0045* | 1.5181 | 0.2189 | 4.0702 | 0.0442* |
| KL Property (KLPR) | 213.0419 | 0.0000* | 0.4327 | 0.5112 | 144.1991 | 0.0000* |
| KL REIT (KLRE) | 197.3107 | 0.0000* | 10.7517 | 0.0012* | 115.3931 | 0.0000* |
| KL Technology (KLTE) | 83.4572 | 0.0000* | 2.0641 | 0.1519 | 46.1574 | 0.0000* |
| KL Telecommunications & Media (KLTC) | 138.0191 | 0.0000* | 0.2318 | 0.6306 | 115.5262 | 0.0000* |
| KL Transportation & Logistics (KLTP) | 203.0173 | 0.0000* | 0.2565 | 0.6130 | 120.2649 | 0.0000* |
| KL Utilities (KLUT) | 146.8426 | 0.0000* | 0.0067 | 0.9347 | 110.5202 | 0.0000* |

*The values are significant at the 5% level.

## 4.4 GARCH Model Result

The results of GARCH models for full and during COVID-19 periods are presented in Tables 7 and 8. Both results for during and full period revealed that the coefficient for ARCH parameters, $\gamma_1$ shows positive and significant values as compared to 5% significant values. It means that today's headlines are affected by the events of the previous day for all sectors. The GARCH parameter coefficient, $\delta_1$ for all sectors are positive and significant. There is a statistically significant GARCH parameter, which suggests that it has conditional variance and a greater impact on volatility. Moreover, findings demonstrate that volatility persistence, assessed by the sum of $\delta_1$ and $\gamma_1$ is closer to one that indicates a larger prevalence of ARCH and GARCH effects. In other words, the current volatility of the daily returns can be explained by the volatility of the past, which tends to continue over time. This result is supported by a study from Sharma (2020) that stated the volatility of the stock market in Singapore has a significant relationship with the COVID-19 period.

Table 7. Variance Equation Parameters for Variables in Full Period Model.

| | $\gamma_0$ | p-value | $\delta_1$ | p-value | $\gamma_1$ | p-value |
|---|---|---|---|---|---|---|
| Kuala Lumpur Composite Index (KLCI) | 0.0100 | 0.0208* | 0.9132 | 0.0000* | 0.0719 | 0.0000* |
| KL Construction (KLCT) | 0.0741 | 0.0000* | 0.8780 | 0.0000* | 0.0840 | 0.0000* |
| KL Consumer Product (KLCM) | 0.0111 | 0.0028* | . 0.8933 | 0.0000* | 0.0879 | 0.0000* |
| KL Energy (KLEN) | - | - | - | - | - | - |
| KL Finance (KLFI) | 0.0302 | 0.0000* | 0.7536 | 0.0000* | 0.2691 | 0.0000* |
| KL Healthcare (KLHC) | 0.0108 | 0.0134* | 0.8979 | 0.0000* | 0.1083 | 0.0000* |
| KL Industrial Product (KLIP) | 0.0219 | 0.0001* | 0.8688 | 0.0000* | 0.1223 | 0.0000* |
| KL Plantation (KLPL) | 0.0192 | 0.0029* | 0.9040 | 0.0000* | 0.0784 | 0.0000* |
| KL Property (KLPR) | 0.0486 | 0.0003* | 0.8557 | 0.0000* | 0.0940 | 0.0000* |
| KL REIT (KLRE) | 0.0628 | 0.0000* | 0.5214 | 0.0000* | 0.2785 | 0.0000* |
| KL Technology (KLTE) | 0.1548 | 0.0003* | 0.8081 | 0.0000* | 0.1439 | 0.0000* |
| KL Telecommunications & Media (KLTC) | 0.0207 | 0.0018* | 0.9133 | 0.0000* | 0.0693 | 0.0000* |
| KL Transportation & Logistics (KLTP) | 0.0268 | 0.0020* | 0.9001 | 0.0000* | 0.0798 | 0.0000* |
| KL Utilities (KLUT) | 0.0133 | 0.0038* | 0.9099 | 0.0000* | 0.0686 | 0.0000* |

*The values are significant at the 5% level.

Table 8. Variance Equation Parameters for Variables in During COVID-19 Period Model.

| | $\gamma_0$ | p-value | $\delta_1$ | p-value | $\gamma_1$ | p-value |
|---|---|---|---|---|---|---|
| Kuala Lumpur Composite Index (KLCI) | 0.0403 | 0.0071* | 0.8682 | 0.0000* | 0.0883 | 0.0000* |
| KL Construction (KLCT) | 0.0410 | 0.0039* | 0.8972 | 0.0000* | 0.0874 | 0.0000* |
| KL Consumer Product (KLCM) | 0.0325 | 0.0241* | . 0.8511 | 0.0000* | 0.1031 | 0.0000* |
| KL Energy (KLEN) | - | - | - | - | - | - |
| KL Finance (KLFI) | 0.1065 | 0.0000* | 0.3802 | 0.0000* | 0.6415 | 0.0000* |
| KL Healthcare (KLHC) | 0.1706 | 0.0009* | 0.8176 | 0.0000* | 0.1483 | 0.0000* |
| KL Industrial Product (KLIP) | 0.0452 | 0.0047* | 0.8499 | 0.0000* | 0.1404 | 0.0000* |
| KL Plantation (KLPL) | 0.0273 | 0.0384* | 0.9093 | 0.0000* | 0.0680 | 0.0000* |
| KL Property (KLPR) | 0.0891 | 0.0016* | 0.8036 | 0.0000* | 0.1266 | 0.0000* |
| KL REIT (KLRE) | 0.0584 | 0.0003* | 0.5566 | 0.0000* | 0.3273 | 0.0000* |
| KL Technology (KLTE) | 0.2080 | 0.0009* | 0.7803 | 0.0000* | 0.1703 | 0.0002* |
| KL Telecommunications & Media (KLTC) | 0.0338 | 0.0028* | 0.8950 | 0.0000* | 0.0856 | 0.0000* |
| KL Transportation & Logistics (KLTP) | 0.0867 | 0.0078* | 0.8524 | 0.0000* | 0.0999 | 0.0003* |
| KL Utilities (KLUT) | 0.0258 | 0.0128* | 0.8582 | 0.0000* | 0.1071 | 0.0000* |

*The values are significant at the 5% level.

## 5. Conclusion and Recommendation

In the analysis of the unit root test for stationarity checking, the ARCH test for the heteroscedasticity in the variance of error, and the final GARCH model, two objectives have been achieved. The first objective is to investigate the effect of the COVID-19 outbreak on the stock market volatility of the Kuala Lumpur Composite Index (KLCI) and 13 sectoral indices. Three full-period models were compared before and during the COVID-19 period. The Kuala Lumpur Composite Index (KLCI) and all 13 sectors were impacted by high volatility during COVID-19, according to the volatility model. The KLCI and other sectors, except for KL Energy (KLEN), experienced a large swing in their stock returns when the market was volatile due to the pandemic. The next objective is to determine which sectors are affected by COVID-19 compared to the KLCI. KLCI has shown negative returns and volatility during the pandemic, while KLCT, KLCM, KLEN, KLFI, KLHC, KLIP, KLPL, KLPR, KLRE, KLTE, KLTC, KLTP, and KLUT show positive and negative returns. Moreover, KLCT, KLCM, KLFI, KLHC, KLIP, KLPL, KLPR, KLRE, KLTE, KLTC, KLTP, and KLUT showed volatility during this period, except for KLEN. It is supported by Liew and Puah's (2020) study, which found that the healthcare and telecommunications sectors are significantly more pandemic-resistant, whereas the pandemic spread has harmed other sectors. Therefore, it can be concluded that COVID-19 had an impact on the stock market in Malaysia, as the market has become slow and stopped, and sectoral activity was paused during the outbreak of this disease. It is revealed that Malaysia experienced slow economic instability during the outbreak.

There are several recommendations that can be made to improve this study in the future to achieve better results on the impact of COVID-19 on the stock market. Firstly, the data on COVID-19 cases and COVID-19 mortality cases can be included in the project. These variables will provide better findings and may influence the stock market volatility. Moreover, the future study may investigate the internal factors that could affect the stock market volatility, such as interest rates, currency exchange rate and crude oil prices during this pandemic. Furthermore, the analysis can be further using a longer COVID-19 period, including the vaccination and new variants of the COVID-19 period. Lastly, the methodology could be extended to another analysis aiming to understand well how far COVID-19 had an impact on the stock market volatility.

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## Author Contribution

Author1 collected the data, conducted the statistical analysis, and interpreted the results. Author2 prepared the literature review, wrote the research methodology, and made a revision of the entire paper.

## Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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