**ENHANCED KNOWLEDGE IN SCIENCES AND TECHNOLOGY**
e-ISSN: 2773-6385

**EKST**

Vol. 4 No. 1 (2024) 21-31
https://publisher.uthm.edu.my/periodicals/index.php/ekst

# Performance Indicators Analysis of Malaysia's Stock Market During COVID-19 Pandemic

**Chia Zhe Yie[1], Kek Sie Long[1]*, Isaudin Ismail[1]**

[1] *Department of Mathematics and Statistics, Faculty Applied Sciences and Technology UTHM Kampus Cawangan Pagoh, Hab Pendidikan Tinggi Pagoh, KM 1, Jalan Panchor, 84600 Pagoh, Muar, Johor, MALAYSIA*

*Corresponding Author: slkek@uthm.edu.my
DOI: https://doi.org/10.30880/ekst.2024.04.01.003

**Article Info**

Received: 27 December 2023
Accepted: 03 June 2024
Available online: 27 July 2024

**Keywords**

Performance indicators, FBMKLCI, COVID-19 pandemic, Augmented Dickey-Fuller test, multiple linear regression, Granger cusality

**Abstract**

The emergence of COVID-19 has affected the stock market in Malaysia and the FTSE *Bursa* Malaysia Kuala Lumpur Composite Index (FBMKLCI). From this point of view, stock price movement influenced by financial and non-financial performance indicators is noticed. In detail, gross domestic product, consumer price index, industrial production index and exchange rate are financial indicators. Meanwhile, the unemployment rate, number of COVID-19 cases, and number of COVID-19 deaths are non-financial indicators. In our study, three objectives are considered. The first is to test the stationarity of data collected by the Augmented Dickey-Fuller test. The second is to identify the impact of the performance indicators on the stock market by multiple linear regression analysis. The third is to determine the relationship between Malaysia's stock market and performance indicators during the COVID-19 pandemic using the Granger causality test. From the analysis results, the multiple linear regression analysis proves that the exchange rate, unemployment rate, and COVID-19 deaths are negatively correlated with the FBMKLCI. The Granger causality test shows a unidirectional Granger relationship between CPI and FBMKLCI.

## 1. Introduction

An unexpected coronavirus (COVID-19) outbreak in China. The Chinese government reported the appearance of a new type of virus to the World Health Organization (WHO) on December 31, 2019, and it was officially announced as a global pandemic on March 11, 2020 [1]. Malaysia is one of the countries affected by the coronavirus. The sharp rise in the number of infections domestically and globally forced the government to enact containment policies, including complete Movement Control Order (MCO), school closures, and border restrictions to restrict the spreading of the virus. The implementation of these policies also restricted economic activity in a country. The development of a nation's economy is directly linked to stock market developments [2]. Hence, the FTSE *Bursa* Malaysia Kuala Lumpur Composite Index (FBMKLCI) experienced a downtrend during the initial phase of COVID-19, as shown in Figure 1 below [3]. The figure shows that the lowest point was 1407.78 in April 2020, while the highest was 1627.21 in December 2020. Fundamentally, FBMKLCI showed a sign of recovery when Malaysia entered the endemic phase on April 1, 2022.

This is an open access article under the CC BY-NC-SA 4.0 license.

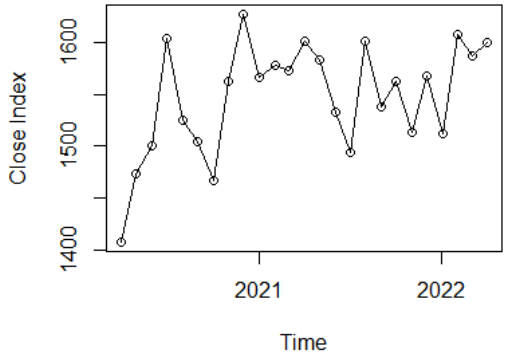


**Fig. 1** *FBMKLCI data from April 2021 – April 2022*

In previous studies, increases in gross domestic product (GDP) and decreases in consumer price index (CPI) significantly increased stock prices by using multiple linear regression analysis [4]. Besides, a positive linkage between industrial production index (IPI) and stock market return was revealed [5]. Moreover, an encouraging connection between the exchange rate and the KLCI was presented using Pearson's coefficient correlation method [6]. Nevertheless, the consistent rise in reported cases and deaths of COVID-19 has negatively influenced stock market returns [7]. Furthermore, a robust one-way causality between the unemployment rate and stock prices was demonstrated in developing countries [8]. Other previous studies were done in using forecasting method with the statistics technique in worldwide according to various fields of studies [9, 10, 11, 12].

In our study, the main focus is the impact of performance indicators of Malaysia's stock market on the stock market's performance. An effective performance measurement system should cover all relevant financial and non-financial performance indicators [13]. Thus, the following performance indicators are considered: gross domestic product (GDP), consumer price index (CPI), industrial production index (IPI), exchange rate, unemployment rate, COVID-19 cases, and deaths. These performance indicators are categorized as independent variables, while the FBMKLCI is dependent. The monthly historical data of FBMKLCI from April 2020 to April 2022 are collected from Open Department of Statistic Malaysia (DOSM), official GitHub account of Ministry of Health Malaysia (MoH), and Market Watch for data analysis. Thus, we have three objectives to study the performance indicators. The first is to test the stationarity of data collected for closing index and financial and non-financial performance indicators using the Augmented Dickey-Fuller (ADF) test. The second is to identify the impact of financial and non-financial performance indicators on the stock market using multiple linear regression analysis. The third is to determine the causal relationship between Malaysia's stock market and performance indicators during the COVID-19 pandemic using the Granger Causality test.

## 2. Material and Methods

In this section, the methodology used to conduct the study is discussed. The monthly historical data of FBMKLCI and the performance indicators, which are gross domestic product (GDP), consumer price index (CPI), industrial production index (IPI), exchange rate, unemployment rate, number of COVID-19 cases, and COVID-19 deaths, are collected from April 2020 to April 2022 from Open Department of Statistic Malaysia (DOSM), official GitHub account of Ministry of Health Malaysia (MoH), and Market Watch.

### 2.1 Augmented Dickey-Fuller Test

The Augmented Dickey-Fuller (ADF) test is an elevated model of the Dickey-Fuller (DF) test to detect the appearance of unit roots. It was explored by Dickey and Fuller in 1979. The equation of the ADF test is stated below [14],

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{m} \delta_i \Delta y_{t-i} + \varepsilon_t, \quad (1)$$

where $\Delta$ is the first difference operation, $y$ is the time series variable, $\alpha$ is a constant, $\beta$ is a coefficient on a time trend, $t$ is the time trend variable, $\gamma$ is a parameter on a time trend, $\delta_i$ is a coefficient on a time trend, $i$ is a lag order and $\varepsilon_t$ is a standard error. The unit root test is conducted with hypothesis testing on the following statement,

$H_0$: Time series data is non-stationary.

$H_1$: Time series data is stationary.

The data is stationary when the null hypothesis is rejected at 5% level of significance. If the null hypothesis is failed to reject, then the logarithm and differencing transformation are employed. The general equation for logarithm transformation is stated below [15],

$$y' = \log(y), \tag{2}$$

where $y'$ is transformed variable and $log$ is natural logarithm. The first and higher order ($d^{th}$ order) differencing are given as below [15],

$$\nabla y_t = y_t - y_{t-1}, \tag{3}$$
$$\nabla^d y_t = (1-B)^d y_t. \tag{4}$$

where $t = 2,3,\dots,n$, $\nabla^d$ is $d^{th}$ order difference operator, $y_t$ is original time series, and $B$ is backshift operator.

## 2.2 Shapiro-Wilk test and Skewness

The Shapiro-Wilk test is one of the popular normality tests with the sample size less than 50. It is a hypothesis testing on the hypothesis statement below,

$H_0$: Data follows a normal distribution.

$H_1$: Data does not follow a normal distribution.

The dependent variable follows a normal distribution when the null hypothesis is failed to reject at 5% level of significance. In R programming, a test statistic, namely Calc $W$ is computed and it can be used to compare with the critical value from the Shapiro-Wilk table, Tab $W$. When Calc $W$ is greater than Tab $W$, then it concludes that the data follows normal distribution [16]. The result can be supported by computing the skewness using the formula below [17],

$$\text{skew} = \frac{3(\bar{x} - \text{median})}{s}, \tag{5}$$

where $\bar{x}$ is the sample mean and $s$ is the sample standard deviation. When the computed skewness value falls between -0.5 and 0.5, then it is nearly symmetric. Hence, the dependent variable follows a normal distribution.

## 2.3 Pearson Correlation Coefficient

The direction and strength of a linear relationship between dependent and independent variables can be identified by the Pearson correlation coefficient, $r$. The Pearson correlation coefficient, $r$ is computed using $R$ studio and its formula is given below [18],

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}, \tag{6}$$

where $\bar{x}$ is the mean of variable $x$ and $\bar{y}$ is the mean of variable $y$. When $r \neq 0$, then there is a linear correlation exist between the dependent and independent variables. If $r = 0$, then there is no linear correlation between the dependent and independent variables.

## 2.4 Standardized Regression Coefficient

The linear relationship can also be explored by computing the standardized regression coefficient, $\hat{\beta}$. The formula of standardized regression coefficient is stated below [19],

$$\hat{\beta_i} = b_i \frac{S_{x_i}}{S_y}, \tag{7}$$

where $b_i$ is the regression coefficient, $S_{xi}$ is the $i$th standard deviation of variable $x$ and $S_y$ is the $i$th standard deviation of variable $y$. The linear relationship is identified by hypothesis testing for the hypothesis statement below,

$H_0$: There is no linear relationship between $y$ and $x_i$, ( $\hat{\beta_i} = 0, i = 1,2,\dots,p$).

$H_1$: There is a linear relationship between $y$ and $x_i$, ( $\hat{\beta_i} \neq 0, i = 1,2,\dots,p$).

A linear relationship exists between response and predictor variables when $\hat{\beta_i} \neq 0$. A regression coefficient with value greater (less) than 0 indicates that there is a positive (negative) linear relationship.

## 2.5 Multiple Linear Regression Model

Multiple linear regression test is the statistical test for examining the correlation between more than two predictor variables (independent) and one response variable (dependent). Generally, the multiple linear regression model's equation is stated below [20],

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p + \varepsilon, \tag{8}$$

where $\beta_i$ for $i$ = 0,1, 2, ..., $p$, are coefficients, $y$ is dependent variable and $x_i$ are independent variables, and $\varepsilon$ is a standard error. The regression model undergoes two partial tests to identify the most statistically significant variables in the model. The first partial test is the hypothesis testing that examines the significance of the independent variable towards the regression model employed. The hypothesis statement is stated below,

$H_0$: Independent variable is not statistically significant to the regression model ($\beta_i = 0, i = 1,2, \ldots, p$)

$H_1$: Independent variable is statistically significant to the regression model ($\beta_i \neq 0, i = 1,2, \ldots, p$)

The second partial test is the hypothesis testing to examine the significance of the constant towards the regression model. The hypothesis statement is stated below,

$H_0$: Constant is not statistically significant to the regression model ($\beta_0 = 0$)

$H_1$: Constant is statistically significant to the regression model ($\beta_0 \neq 0$)

The independent variable and constant can be categorized as a significant value in the model when the null hypothesis is rejected at 5% significance level. The insignificant variable will be manually eliminated from the model starting from the least significant variable until all variables are statistically significant to the model.

Furthermore, a best-fit regression model is selected by comparing three criteria including the coefficients of determinant ($R$-squared), corrected Akaike Information Criterion (AICc) and Bayesian Information Criterion (BIC). The model with the highest $R$-squared, lowest AICc and BIC is the best-fit model. The impact of the performance indicators on the stock price can be analysed through the model.

## 2.6 Granger Causality test

The Granger causality test is applied to investigate the relationship of causation and effect between two variables in a time series. We carried out the test on the bivariate system since we examined the causal relationship between two-time series. It is categorized into restricted and unrestricted model. The general equation for these two models is given below [21],

$$x(t) = c_1 + \sum_{i=1}^{\infty} \alpha_i x(t-i) + u_1(t), \tag{9}$$

$$y(t) = c_1 + \sum_{i=1}^{\infty} \alpha_i y(t-i) + v_1(t), \tag{10}$$

$$x(t) = c_2 + \sum_{i=1}^{\infty} \alpha_i x(t-i) + \sum_{j=1}^{\infty} \beta_j y(t-j) + u_2(t), \tag{11}$$

$$y(t) = c_2 + \sum_{i=1}^{\infty} \alpha_i y(t-i) + \sum_{j=1}^{\infty} \beta_j x(t-j) + v_2(t), \tag{12}$$

where $\beta_i$ for $i$ = 0,1, 2, ..., $p$, are coefficients, $y$ is dependent variable and $x_i$ are independent variables, and $\varepsilon$ is a standard error.

The hypothesis testing is conducted to examine the Granger relationship. The hypothesis statement is given below,

$H_0$: $x_t$ does not granger cause $y_t$ or $y_t$ does not granger cause $x_t$

$H_1$: $x_t$ granger cause $y_t$ or $y_t$ granger cause $x_t$

A Granger relationship exists when the null hypothesis is rejected at a 5% significance level. Four potential outcomes that are no causality, two-way causality, $x_t$ granger cause $y_t$, and $y_t$ granger cause $x_t$.

## 3. Results and Discussion

This section uses R programming to carry out the data analysis, and the test result is presented.

## 3.1 Data Preprocessing

Before analysing the data, data cleaning must be performed. The outliers are removed from the dataset. The equation below (13) can determine the outliers,

$$\text{First quartile, } Q_1 = \frac{1}{4}(n+1) \text{ term,} \tag{12}$$

$$\text{Third quartile, } Q_3 = \frac{3}{4}(n+1) \text{ term,} \tag{13}$$

$$\text{Interquartile Range, IQR} = \text{Q}_3\text{-Q}_1, \tag{14}$$

$$\text{Lower Bound} = Q_1 - 1.5\,(IQR), \tag{15}$$

$$\text{Upper Bound} = Q_3 + 1.5\,(IQR), \tag{16}$$

where $n$ is the number of observations. The data out of the lower and upper bound range are removed. Table 1 shows the result of outlier detection. The FBMKLCI, CPI, and unemployment rate do not exhibit outliers in the dataset. However, multiple outliers are detected in the dataset for the remaining variable. It is necessary to remove these outliers from the particular dataset.

**Table 1** *Result of Outlier Detection*

| Variables | $Q_1$ | $Q_3$ | IQR | Lower Bound | Upper Bound | Does the dataset contain outlier? |
|---|---|---|---|---|---|---|
| FBMKLCI | 1512.27 | 1587.36 | 75.09 | 1399.635 | 1699.995 | No |
| GDP | 336161 | 360151 | 23990 | 300176 | 396136 | Yes |
| CPI | 120.1 | 123.7 | 3.6 | 114.7 | 129.1 | No |
| IPI | 114.745 | 120.4772 | 5.7322 | 106.1467 | 129.0755 | Yes |
| ER | 0.237528 | 0.242483 | 0.004955 | 0.230096 | 0.249915 | Yes |
| UR | 0.043 | 0.048 | 0.005 | 0.0355 | 0.0555 | No |
| NC | 20324 | 225947 | 205623 | -288110.5 | 534381.5 | Yes |
| DC | 97 | 1513 | 1416 | -2027 | 3637 | Yes |

## 3.2 Data Stationarity

Table 2 shows the results of the Augmented Dickey-Fuller test. The null hypothesis is rejected since the $p$-value is 0.02177, smaller than 0.05. Hence, FBMKLCI is stationary at a 5% level of significance. The remaining variables are required to be transformed, and the stationarity test is conducted.

**Table 2** *Results of Augmented Dickey-Fuller test*

| Variables | Level | Logarithm Transformation | First Difference Transformation |
|---|---|---|---|
| FBMKLCI | -4.0425 | -4.0609 | -6.3046 |
| | (0.02177) | (0.02113) | (<0.01) |
| GDP | -1.8309 | -1.8064 | -2.9797 |
| | (0.6368) | (0.6461) | (0.1992) |
| CPI | -2.6254 | -2.5912 | -3.1075 |
| | (0.3341) | (0.3471) | (0.1515) |
| IPI | -1.884 | -1.8758 | -2.1253 |
| | (0.6166) | (0.6197) | (0.5247) |
| ER | -2.9082 | -2.935 | -2.8117 |
| | (0.2264) | (0.2162) | (0.2632) |
| UR | -1.5809 | -1.3772 | -3.5299 |
| | (0.732) | (0.8096) | (0.09724) |
| NC | -2.7585 | -1.9768 | -3.2095 |
| | (0.2834) | (0.5812) | (0.1116) |
| DC | -1.8248 | -1.2016 | -2.686 |
| | (0.6391) | (0.8765) | (0.3111) |

Table 3 shows the results of the differencing transformation. Notice that the $p$-value for the remaining indicators is smaller than 0.05. As a result, the variables are stationary at a 5% significance level. After three times of differencing transformation, most variables reach a stationary state except the exchange rate (ER) and unemployment rate (UR).

**Table 3** *Results of differencing transformation*

| Variables | Number of differences | $t$-statistic and $p$-value |
|---|---|---|
| GDP | 3 | -3.9974 (0.02335) |
| CPI | 3 | -4.0802 (0.02046) |
| IPI | 3 | -4.2753 (0.01365) |
| ER | 2 | -6.407 (< 0.01) |
| UR | 4 | -4.0113 (0.02286) |
| NC | 3 | -3.6138 (0.04902) |
| DC | 3 | -4.1337 (0.01859) |

## 3.3 Normality and Skewness

After conducting the Shapiro-Wilk test, the $p$-value is 0.2205, more significant than 0.05, and the null hypothesis failed to reject. Thus, FBMKLCI follows the normal distribution at a 5% significance level. Another statistic obtained from the R programming is shown in Table 4. The statistic proves the dependent variable follows a normal distribution since Calc $W$ > Tab $W$.

**Table 4** *Results of Shapiro-Wilk test*

| Sample size, $n$ | Significance level, $\alpha$ | Calc $W$ | Tab $W$ |
|---|---|---|---|
| 19 | 0.05 | 0.93571 | 0.901 |

The summary of the skewness of FBMKLCI is shown in Table 5. Since its skewness is 0.523927, it is nearly symmetrical. Thus, we may conclude that FBMKLCI follows a normal distribution.

**Table 5** *Summary of skewness of FBMKLCI*

| Sample mean, $\bar{x}$ | Median | Sample standard deviation, $s$ | Skewness |
|---|---|---|---|
| 0.002765 | -0.144847 | 0.8451538 | 0.52397 |

## 3.4 Correlation Analysis

Table 6 shows the Pearson correlation coefficient, $r$, for FBMKLCI and GDP, CPI, and COVID-19 cases (NC) are 0.4894, 0.2347, and 0.0945, respectively. Therefore, a weak positive correlation exists between these variables. Besides, IPI and COVID-19 deaths (DC), with $r = -0.3284$ and $r = -0.05321$, respectively, have a negative linear correlation with FBMKLCI. The Pearson correlation coefficient for the exchange rate and unemployment rate are -0.5299 and -0.6536, respectively. Therefore, a modest negative correlation exists between FBMKLCI and these two variables since their r value falls between -0.7 and -0.5. Overall, a linear relationship exists between the dependent and independent variables.

**Table 6** *Pearson correlation coefficient*

| Dependent Variable, $y$ | Independent variable, $x_i$ | Pearson correlation coefficient, $r$ | Linear relationship |
|---|---|---|---|
| FBMKLCI | GDP | 0.4894 | Weak positive linear correlation |
| | CPI | 0.2347 | Weak positive linear correlation |
| | IPI | -0.3284 | Weak negative linear correlation |
| | ER | -0.5299 | Modest negative linear correlation |
| | UR | -0.6536 | Modest negative linear correlation |
| | NC | 0.0945 | Weak positive linear correlation |
| | DC | -0.05321 | Weak negative linear correlation |

## 3.5 Hypothesis Testing on Linearity

Table 7 shows the result of the standardized regression coefficients, $\hat{\beta}$. The result proves that linear relationships exist between FBMKLCI and all the independent variables since $\hat{\beta} \neq 0$. A positive linear relationship appears between FBMKLCI and CPI and FBMKLCI and NC due to the positive value of the standardized regression coefficient, $\hat{\beta}$. However, the remaining independent variables, GDP, IPI, ER, UR, and DC, have a negative linear relationship with the FBMKLCI.

**Table 7** *Standardized regression coefficients*

| Dependent Variable, $y$ | Independent variable, $x_i$ | Standardized regression coefficient, $\hat{\beta_i}$ |
|---|---|---|
| FBMKLCI | GDP | -0.07927 |
| | CPI | 0.44075 |
| | IPI | -0.16041 |
| | ER | -0.55639 |
| | UR | -0.61465 |
| | NC | 0.13542 |
| | DC | -0.44848 |

Notice that the linear relationship between GDP and FBMKLCI indicated by Pearson correlation coefficient, $r$ and standardized regression coefficient, $\hat{\beta}$ are different. This is because the Pearson correlation coefficient, $r$ measures the linear relationship between two variables only. The computed value shows a simple correlation between GDP and FBMKLCI. However, the standardized regression coefficient, $\hat{\beta}$ consider the scale of the remaining independent variables in the model.

## 3.6 Linear Relationship

The best-fit model is chosen by comparing the $R$-squared, AICc, and BIC. Table 8 shows the result of the model selection. Model 6 is the best-fit model since it satisfies two criteria: the lowest AICc and BIC. Model 6 proves that the exchange rate, unemployment rate and COVID-19 deaths react negatively to Malaysia's stock market, where the reduction of these three performance indicators boosts the closing index.

**Table 8** *Results of model selection*

| Model | Variables in model | $R$-squared | AICc | BIC |
|---|---|---|---|---|
| Model 1 | GDP, CPI, IPI, ER, UR, NC, DC, constant | 0.8395 | 49.74 | 38.23644 |
| Model 2 | CPI, IPI, ER, UR, NC, DC, constant | 0.8370 | 42.43 | 35.58734 |
| Model 3 | CPI, ER, UR, NC, DC, constant | 0.8305 | 36.96 | 33.38754 |
| Model 4 | CPI, ER, UR, DC, constant | 0.8129 | 33.66 | 32.32288 |
| Model 5 | ER, UR, DC, constant | 0.7620 | 33.84 | 33.94853 |
| Model 6 | ER, UR, DC | 0.7582 | 30.38 | 31.30539 |

Table 9 shows the result of the estimated Model 6. The $p$-values of the exchange rate, unemployment rate, and COVID-19 deaths in this model are 0.000255, 0.000255, and 0.028839, respectively. These independent variables can be considered significant in the model due to their relatively low $p$-value. The estimated coefficient indicates that when the exchange rate increases by one unit, the closing index will decrease by 29.66 units. Besides, the closing index is reduced by 1.25 units for every additional unit in the unemployment rate. While each unit increase in the number of COVID-19 deaths corresponds to a 0.16 unit decline in the closing index.

**Table 9** *Results of estimated sixth model*

| Independent variables, $x_i$ | Estimated coefficient, $\beta_i$ | $t$-stat | $p$-value |
|---|---|---|---|
| ER | -29.65574 | -4.672 | 0.000255 |
| UR | -1.24755 | -4.672 | 0.000255 |
| DC | -0.16131 | -2.401 | 0.028839 |

Figure 2 shows the plot for the sixth regression model, where the FBMKLCI reacts inversely with the exchange rate, unemployment rate, and number of deaths.

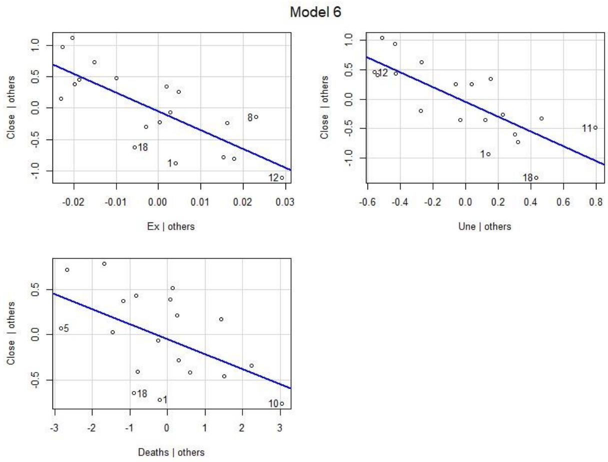


**Fig. 2** *Plot of Model 6*

Table 10 shows the result of estimating the Model 1. The $p$-values of the exchange and unemployment rates are 0.0161 and 0.0109, which are smaller than $\alpha$ = 0.05. As a result, the null hypothesis is rejected at a 5% significance level. Hence, these two variables are statistically significant to the model.

**Table 10** *Results of estimated Model 1*

| Independent variables, $x_i$ | Estimated coefficient, $\beta_i$ | $t$-stat | $p$-value |
|---|---|---|---|
| (Intercept) | -0.07146 | -0.707 | 0.4943 |
| GDP | -0.99890 | -0.415 | 0.6860 |
| CPI | 9.00795 | 1.767 | 0.1049 |
| IPI | -0.56432 | -0.516 | 0.6163 |
| ER | -23.59403 | -2.840 | 0.0161 |
| UR | -1.31199 | -3.057 | 0.0109 |
| NC | 0.09626 | 0.753 | 0.4672 |
| DC | -0.20017 | -1.958 | 0.0760 |

Figure 3 shows the plot for the first regression model. It indicates that FBMKLCI is negative with GDP, IPI, exchange rate, unemployment rate, and number of deaths. In contrast, FBMKLCI is positive for CPI and the number of COVID-19 cases.

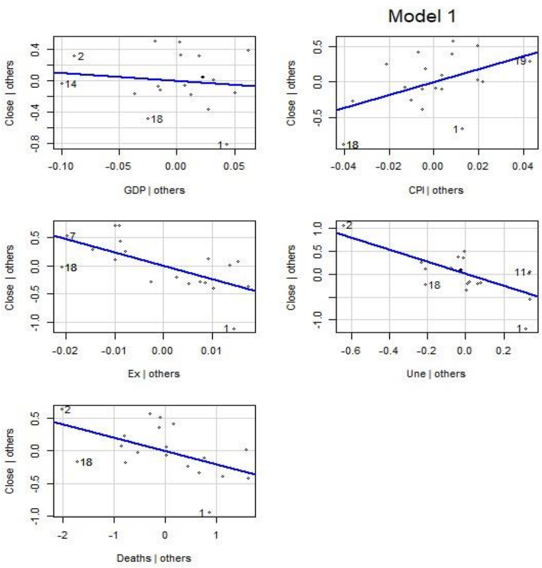


**Fig. 3** *Plot of Model 1*

The sequence has eliminated the GDP, IPI, COVID-19 cases, and CPI due to their relatively high $p$-values. Lastly, the $y$-intercept value has also been removed from the regression model.

## 3.7 Granger Relationship

Figure 4 shows the Granger relationship at a 5% significance level. By observing the figure, the consumer price index can be employed to forecast the closing index, gross domestic product, and unemployment rate, but not vice versa. The consumer price index can be predicted through the exchange rate, but the reverse way does not hold. The exchange rate can be predicted using the number of deaths during crisis time, but the exchange rate cannot expect the deaths. A one-way Granger causal relationship from gross domestic product to the unemployment rate proves that gross domestic product can forecast the unemployment rate in future. A bidirectional relationship appears between the unemployment rate and industrial production index. Overall, the consumer price index is the only performance indicator with a direct Granger relationship to the closing index.

Notably, there is no direct one-way or two-way causality between the non-financial indicators and the closing index. Hence, non-financial indicators are not encouraged to be applied in forecasting future stock prices.

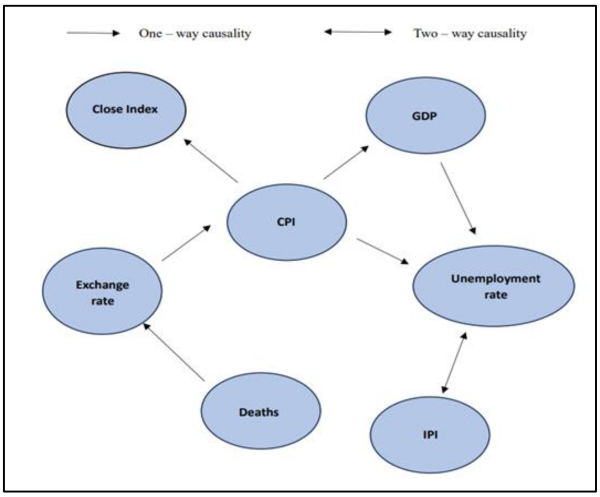


**Fig. 4** *Granger causal relationship at 5% level of significance*

## 4. Conclusion

This paper analysed the performance indicators of the stock market in Malaysia during the COVID-19 pandemic. These performance indicators, which are gross domestic product (GDP), consumer price index (CPI), industrial production index (IPI), exchange rate, unemployment rate, COVID-19 cases, and deaths, were categorized as the independent variables, and the FBMKLCI was dependent. Several statistical tests were conducted: stationarity, normality, skewness, and correlation. The linear relationship was investigated throughout the correlation analysis, and the multiple linear regression models were constructed. The best-fit model illustrated the negative linear relationship of FMBKLCI with the exchange rate, unemployment rate and COVID-19 deaths. From the Granger relationship, the consumer price index was the leading indicator to forecast the closing index, gross domestic product, and unemployment rate, but not vice versa. In the end, studying and comparing the stock indexes from different countries is recommended for future research. The impact on stock markets before and after the pandemic shall be analysed quantitatively for comprehensive findings and a better understanding to investigators.

## Acknowledgement

The authors would thank the Faculty of Applied Sciences and Technology, Universiti Tun Hussein Onn Malaysia for its support.

## Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

## Author Contribution

*The authors confirm contribution to the paper as follows: study conception and design: Chia Zhe Yie and Isaudin Ismail;* ***data collection:*** *Chia Zhe Yie;* ***analysis and interpretation of results:*** *Chia Zhe Yie, Kek Sie Long;* ***draft manuscript preparation:*** *Chia Zhe Yie. All authors reviewed the results and approved the final version of the manuscript.*

## References

[1] WHO. (2020, April 27). Archived: WHO Timeline - COVID-19. https://www.who.int/news/item/27-04-2020-who-timeline---covid-19

[2] Patil, S., & Bagodi, V. (2021). A Study of Factors affecting Investment Decisions in India: The KANO Way, *Asia Pacific Management Review,* 26(4), 197-214. https://doi.org/10.1016/j.apmrv.2021.02.004

[3] Market Watch. (2023). *Download FBMKLCI Data |FTSE Bursa Malaysia Price Data* [Data Set]. https://www.marketwatch.com/investing/index/fbmklci/download-data?startDate= 1/1/2022&endDate =12/31/2022&countryCode=my

[4] Huy, D. T., Loan, B. T., & Anh, P. T. (2020). Building An Econometric Model of Selected Factors' Impact On Stock Price: A Case Study, *Journal of Entrepreneurship and Sustainability Issue,* 9(May), 77-93. http://doi.org/10.9770/jssi.2020.9.M(7)

[5] Jareño, F., Escribano, A., & Cuenca, A. (2019). Macroeconomic Variables and Stock Markets: An International Study, *Applied Econometrics and International Development,* 19(1), 43-54. https://www.usc.gal/economet/reviews/aeid1914.pdf

[6] Rosbi, S., & Haji-Othman, Y. (2020). Economic Recovery of post COVID-19 towards Kuala Lumpur Composite Index (KLCI) and Malaysian Ringgit Exchange Rate, *International Conference on Contemporary Issues in Islamic Finance (e- ICCIIF 2020)*. https://www.researchgate.net/profile/Yusuf-Haji-Othman/publication/344738510_Economic_ Recovery_ of_ post_ COVID-19_ towards _Kuala_ Lumpur_ CompositeIndex_KLCI_and_Malaysian_Ringgit_Exchange_Rate/links/5f8d37ad458515b7cf8b5c68/Economic-Recovery-of-post-COVID-19 -towards- Kuala- Lumpur- Composite- Index -KLCI-and-Malaysian-Ringgit-Exchange-Rate.pdf

[7] Guven, M., Cetinguc, B., Guloglu, B., & Calisir, F. (2022). The Effects of Daily Growth in COVID-19 Deaths, Cases, and Governments' Response Policies On Stock Markets of Emerging Economies, *Research in International Business and Finance,* 61(2022), 101659. https://doi.org/10.1016/j.ribaf.2022.101659

[8] Pan, W.-F. (2018). Does the Stock Market really cause Unemployment? A Cross-country Analysis, *The North American Journal of Economics and Finance,* 44, 34–43. https://doi.org/10.1016/j.najef.2017.11.002

[9] Loo, K., & Asrah, N. M. (2022). Survey on Customer Satisfaction Towards Courier Services in Johor. *Enhanced Knowledge in Sciences and Technology*, *2*(2), 186-196.

[10] Zulkiflee, N. F., & Rusiman, M. S. (2021). Heart Disease Prediction Using Logistic Regression. *Enhanced Knowledge in Sciences and Technology*, *1*(2), 177-184.

[11] Lim, L. S. Y. S., & Ismail, T. D. I. B. (2022). A Study On Volatility and Tail Risk of Small-Cap Companies in Comparison to Big-Cap Companies. *Enhanced Knowledge in Sciences and Technology*, *2*(1), 241-249.

[12] Haron, N. A. A., & Kamardan, M. G. (2021). Queuing system of a busy restaurant using simulation software. *Enhanced Knowledge in Sciences and Technology*, *1*(2), 66-71.

[13] Rashid, N. M., Noor, R. M., Matsuki, N., AbRahman, N. A., & Omar, N. (2016). The Longitudinal Study of Earnings Management: Analysis on Companies Financial Abilities, *Procedia Economics and Finance,* 35(2016), 136-145. https://doi.org/10.1016/S2212-5671(16)00018-6
[14] Robert, A. Y., & Monnie, M. (2009). *Introduction to Time Series Analysis and Forecasting : With Applications of SAS and SPSS.* Academic Press. https://books.google.com.my/books?id= LSojZBiBZBgC&lpg =PP2&ots=MskQGeUXT2&lr&pg=PP2#v=onepage&q&f=false
[15] Shumway, R. H., & Stoffer, D. S. (2011). *Time Series Analysis and Its Applications with R Examples.* Springer. http://dx.doi.org/10.1007/978-1-4419-7865-3
[16] King, A. P., & Eckersley, R. J. (2019) *Statistics for Biomedical Engineers and Scientists: How to Visualize and Analyze Data.* Elsevier Science. https://doi.org/10.1016/B978-0-08-102939-8.00016-5
[17] Ramalingam, S., & Rajan, C. (2015). *Statistics For Scientific And Engineers.* John Wiley & Sons, Incorporated. http://ndl.ethernet.edu.et/bitstream/123456789/33281/1/Ramalingam%20Shanmugam_2015.pdf
[18] Taeger, D., & Kuhnt, S. (2014). *Statistical hypothesis testing with SAS and R*. John Wiley & Sons, Incorporated. https://ebookcentral.proquest.com/lib/uthm-ebooks/detail.action?docID=1602290
[19] Andrew, F. S., & Michael, R. W. (2022). *Practical Business Statistics (Eighth Edition). Chapter 12: Multiple Regression- Predicting One Variable from Several Other*. Academic Press. https://doi.org/10.1016/B978-0-12-820025-4.00012-9
[20] Bruce, L. B., Richard, T. O., & Emily, M. (2014). *Regression Analysis : Unified Concepts, Practical Applications, Computer Implementation*. Business Expert Press. https://ebookcentral.proquest.com/lib/uthm-ebooks/detail.action?docID=3002852
[21] Cromwell, J. B., Michael, J. H., Walter, C. L., & Michel, T. (1994). *Multivariate Tests for Time Series Models.* Sage Publications, Inc. https://books.google.com.my/books?id=_1Ohg5mPXLQC&lpg=PP7&ots=G3lMYfe2to &dq=Multivariate%20Tests%20for%20Time%20Series%20Models%20&lr&pg=PP7#v=onepage&q=Multivariate%20Tests%20for%20Time%20Series%20Models&f=false