eISSN: 2637-1138

THE IMPACT OF MACROECONOMIC VARIABLES ON STOCK PRICES: A CASE STUDY FROM FTSE BURSA MALAYSIA KLCI FROM 1994 UNTIL 2022

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https://doi.org/10.46754/umtjur.v8i1.542
Received: 25 July 2024 Revised:14 September 2024 Accepted: 14 November 2024 Published: 15 April 2025

Abstract: This study uses monthly historical data to analyse the effects of changes in selected macroeconomic variables on the stock prices of the FTSE Bursa Malaysia KLCI from 1994 to 2022. A multiple regression model employing Ordinary Least Squares (OLS) and the Granger Causality test are employed to study this relationship. Upon evaluating the estimated regression coefficients and corresponding t-statistics, the findings reveal changes in the prices of Brent Crude Oil (BC) futures. Meanwhile, the Currency Exchange Rates (CR) indicate a significantly positive influence on stock prices. In contrast, the rates of Gross Domestic Product (GDP), Interest Rates (IR), and Inflation Rates (CPI) do not significantly influence stock prices. Additionally, unidirectional Granger Causality is observed between stock prices, the rates of GDP, and the CR.

Keywords: Undergraduate research, stock prices, macroeconomic variables, multiple linear regression, Ordinary Least Squares (OLS).

Introduction

The stock market in Kuala Lumpur, Malaysia, is largely reflected by the FTSE Bursa Malaysia Kuala Lumpur Composite Index (KLSE). Nonetheless, investors frequently fail to achieve their intended returns from their investments since stock market trading is unpredictable, as the market frequently reacts to changes in macroeconomic factors and occasionally for inexplicable reasons. There are other studies on some macroeconomic factors; however, this study will cover some other factors that are seemingly related or weakly related to the stock market but are often prone to having a relationship. Note that understanding changes in some macroeconomic factors and international stock indices is crucial to better predict and forecast changes in the local index, both in the long and short run. As a result, investors can utilise information from the stock market to forecast KLSE's behaviour. Furthermore, by stabilising the stock market, Malaysian authorities can use stock prices as a policy instrument to attract international portfolio investments.

The stock market in Malaysia contributes to the most efficient deployment of capital resources among different users. Stock market returns are returns from stocks listed in Bursa Malaysia. The main index used as the market return indicator is the FTSE Bursa Malaysia KLCI, which comprises 30 companies listed on the Main Board by full market capitalisation (FTSE Russell, 2022). The KLSE highly reflects the stock market in Malaysia (Murthy *et al.*, 2016).

Regression, first introduced in the 19th century by Francis Galton (Kutner *et al.*, 2005), describes relationships between variables. It measures the relation between the mean value of a dependent variable and the corresponding values of other independent variables. Notably, relationships among variables can be described using a statistical technique named regression analysis. At the same time, a linear regression consists of one independent variable, and a multiple linear regression consists of more than one independent variable. Ghozali (2018) assessed the effectiveness of more than one independent variable on the dependent variable using multiple linear regression. In addition, Amanda *et al*. (2023) and Ilham *et al*. (2023) also applied this method to obtain the influences of the independent variables on the dependent variables on the profit management and financial performance of a company value and stock price of the transportation sub-sector in Indonesia. Other studies analyse the effect of economic variables on stock market returns (Patra & Poshakwale, 2006; Raja & Kalyanasundaram, 2010; Owusu-nantri & Kuwornu, 2012; Talla, 2013).

A trend is the overall direction of a market or an asset's price, whether an uptrend or a downtrend. Accordingly, predicting the trend that a stock will follow within a fixed period due to previous predetermined factors is crucial to investors. To better predict and forecast changes in the local index in the long and short run, it is critical to comprehend changes in some macroeconomic elements and international stock indices. As a result, investors may forecast the behaviour of the KLSE using information from the stock market. Stock prices may also be utilised as a policy tool to encourage overseas portfolio investments by stabilising the stock market. For instance, Bhuriya *et al*. (2017) forecasted the behaviour of the TCS data set using linear regression in stock market prediction.

While work by Khan and Khan (2018) and Jamaludin *et al*. (2017) studied the Pakistan Stock Exchanges and ASEAN countries, respectively, many studies have studied the effect of macroeconomic factors focusing on the Malaysia stock market. Moreover, Siang and Rayappan (2023) studied the effects of the Inflation Rates (CPI), real effective exchange rate, money supply, and short-term Interest Rate (IR). Meanwhile, Kalam (2020) studied the effects of Gross Domestic Product (GDP), IR, inflation, exchange rate, and foreign direct investment. On the other hand, Khong *et al*. (2019) included both local and foreign macroeconomic variables.

This study adopts the five most frequent macroeconomic variables in the stock market: Consumer Price Index (CPI), GDP rate, IR, Currency Exchange Rate (CR), and Brent Crude Oil Price (BC), considering both internal and external factors affecting the stock price of a company. Furthermore, to determine the significance of these variables to the Malaysian stock market, we develop a model equation to fit specific macroeconomic factors within a fixed period for predicting the KLSE via Ordinary Least Squares (OLS). This study is organised as follows. Section 2 outlines the methods and techniques used in this study. Section 3 documents the data analysis and discussion of the findings. Section 4 concludes the study.

Data and Methodology

Data

In this study, we utilised monthly historical prices of 30 constituents listed in the FTSE Bursa Malaysia KLCI from the year 1994 to 2022. The data is divided into two sub-groups: Stock data and macroeconomic factors, available from sources as tabulated in Table 1. Data cleaning is first performed on the data set.

Table 1: Sources of data

Sources	Data Available
Yahoo! Finance (https://finance.yahoo.com/)	FTSE KLCI (KLSE)
Trading Economics (https://tradingeconomics.com/)	Brent Crude Oil Price Futures (BC)
Bank Negara Malaysia (https://www.bnm.gov.my/)	Consumer Price Index of Malaysia (CPI), Rate of Gross Domestic Product of Malaysia (GDP), Real Interest Rate of Malaysia (IR)
Index Mundi (https://www.indexmundi.com/)	Real Broad Effective Exchange Rate (CR)

The data ranges from 1994 to 2022. This 29-year range of data consists of 348 months of monthly data. The FTSE Bursa Malaysia KLCI is represented by an adjusted closing price, which indicates the worth of the stock after considering any corporate activities. The adjusted closing price is crucial as it offers investors a more current and accurate idea of the stock's price. Hence, it is frequently applied when examining historical returns or previous performance.

Table 2 lists all descriptive statistics with some details regarding the dependent and independent variables. It indicates that all variables exhibit a positive mean return, where GDP has the highest mean of 11.2662 (Table 2). This implies that Malaysia has a strong economic growth rate and has the potential to impact stock market growth. Conversely, the impact of inflation is the lowest at 0.6533, which suggests that Malaysia's government debt is at a relatively risky and slightly high level. Simultaneously, the CPI has the lowest median of 0.7036, while GDPs have the highest mean in the median section of 11.3059. It indicates that the lowest maximum point for the outcome is 0.7036. However, no data is volatile, as all standard deviations are low. Only the exchange rate of currency has return distributions that are positively skewed, implying that they have a long right tail. Hence, the Jarque-Bera normality test rejects the assumption of normality.

Table 2: Summary statistics for descriptive analysis

Statistics	LKLSE	LCPI	LGDP	LCR	LIR	LBC
Mean	3.06243	0.65330	11.26620	1.98785	0.82904	1.65930
S. E.	0.00875	0.03053	0.04851	0.00235	0.05250	0.01567
Median	3.09519	0.70355	11.30590	1.98686	0.91380	1.72843
Std. Dev.	0.16326	0.16441	0.26124	0.04386	0.27280	0.29240
Sample Var.	0.02665	0.02703	0.06825	0.00192	0.07442	0.08550
Kurtosis	- 0.35731	8.26586	-1.62378	0.45236	2.08785	- 1.13175
Skewness	- 0.64047	- 2.34839	-0.21014	0.75343	- 1.34688	- 0.32671
Range	0.79347	0.88665	0.77921	0.19970	1.22235	1.12607
Minimum	2.48131	0.00000	10.85834	1.91661	0.00000	1.01953
Maximum	3.27478	0.88665	11.63755	2.11631	1.22235	2.14560

Methodology

The return on the FTSE Bursa Malaysia KLCI (KLSE) is the dependent variable, denoted by $\hat{Y}$. The explanatory variables considered in this study are defined as such:

x_1 = CPI = Inflation Rate (Consumer Price Index of Malaysia)
x_2 = GDP = Rate of Gross Domestic Product (GDP of Malaysia)
x_3 = IR = Interest Rate (Real Interest Rate of Malaysia)
x_4 = CR = Currency Exchange Rate (Real Broad Effective Exchange Rate)
x_5 = BC = Oil Price (Brent Crude Oil Price Futures)

Hence, we set the multiple linear regression equation of the model as follows:

$$\hat{Y} = B_0 + B_1 x_1 + B_2 x_2 + B_3 x_3 + B_4 x_4 + B_5 x_5 + \varepsilon \quad (1)$$

where B_0 is the intercept, B_i, $1 \leq i \leq 5$ are coefficients to be estimated, and ε is the error term. Moreover, we assume the following hypotheses:

H_0: Macroeconomic variables significantly affect the stock market return of Bursa Malaysia's performance.

H_1: The inflation rate has a positive relation and effect on the stock market return of Bursa Malaysia's performance.

H_2: The rate of gross domestic product significantly affects the stock market return of Bursa Malaysia's performance.

H_3: Changes in interest rates have a relationship with the stock market return of Bursa Malaysia's performance.

H_4: Currency exchange rates affect the stock market return on Bursa Malaysia's performance.

H_5: Oil prices have a significant effect on the stock market return of Bursa Malaysia's

This study employs the OLS method to analyse the relationship between the FTSE Bursa Malaysia KLCI and the five macroeconomic variables considered. Additionally, the Granger Causality test is also conducted to investigate the individual connection between FTSE Bursa Malaysia KLCI and each of the explanatory variables. Nonetheless, we first perform the unit root test to verify the stationary of the time series data, which is subject to spurious regression if the data is non-stationary. For any non-stationary data reported, the first difference of the variables will be taken before utilising the OLS method and the Granger Causality test.

Analysis and Results

Unit Root Test

Note that non-stationary data can cause spurious regression between unrelated variables. Hence, it is crucial to examine for the presence of a unit root in the series data. Moreover, the existence of non-stationary variables can lead to misleading results, suggesting a high correlation where none exists. Therefore, we first test for unit roots to ensure the data is stationary before performing the OLS method and the Granger Causality tests. For this purpose, we consider the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979; Elder & Kennedy, 2001). The null and alternative hypotheses are as follows:

$H_0 : \rho = 1$ Unit root (variable is non-stationary).

$H_1 : \rho < 1$ No unit root (variable is stationary).

The null hypothesis is rejected if the coefficient is strictly less than 1, which implies that the data series is stationary. Otherwise, it can be concluded that the series is non-stationary; hence, it has a unit root.

Figure 1 plots the variables to identify any trend. The GDP and BC time series have an obvious upward trend, while CR has an obvious downward trend. The mean of KLSE implies stationary, and the mean of CPI and IR are constant over time. Hence, we run the ADF test at a level with trend and intercept.

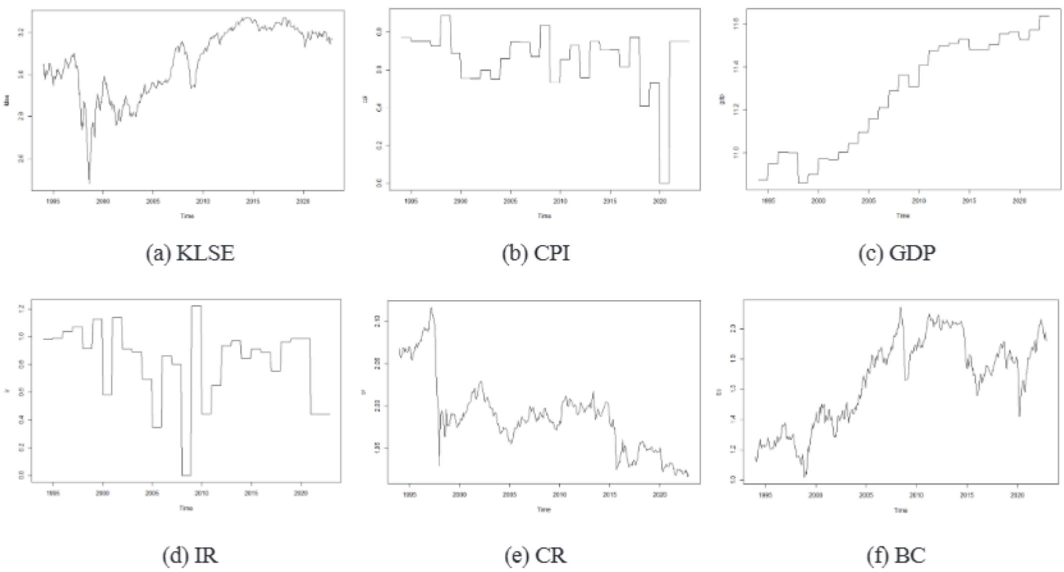


Figure 1: Time series plot of variables

Table 3 indicates that all variables, except for CPI and IR, had *p*-values of more than the 5% critical value. Hence, the null hypothesis cannot be rejected for four out of six variables, implying that these are non-stationary.

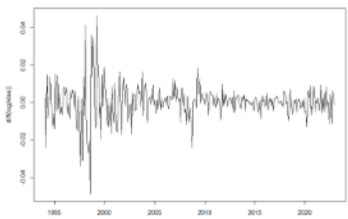
Table 3: ADF test at level, trend, and intercept

Null Hypothesis	*p*-value	Null Hypothesis	Results
KLSE is non-stationary	0.08836	Do not reject	KLSE is non-stationary
CPI is non-stationary	0.01	Reject	CPI is stationary
GDP is non-stationary	0.6701	Do not reject	GDP is non-stationary
IR is non-stationary	0.01	Reject	IR is stationary
CR is non-stationary	0.09392	Do not reject	CR is non-stationary
BC is non-stationary	0.5468	Do not reject	BC is non-stationary

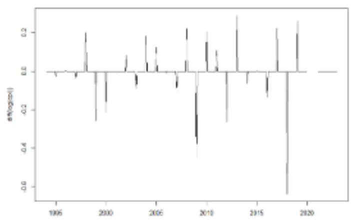
Following that, the first difference of those variables is first determined before including them in the regression model. The summary of the results is tabulated in Table 4. Taking the first difference, the *p*-values for KLSE, GDP, CR, and BC are less than the 5% critical value. Hence, we reject the null hypothesis, implying that those variables are stationary at the first difference. Moreover, the trend in the variables does not exist at the first difference, as can be observed in Figure 2.

Table 4: ADF test at first difference

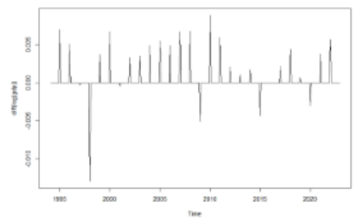
Null Hypothesis	*p*-value	Null Hypothesis	Results
KLSE is non-stationary	0.01	Reject	KLSE is stationary
GDP is non-stationary	0.01	Reject	GDP is stationary
CR is non-stationary	0.01	Reject	CR is stationary
BC is non-stationary	0.01	Reject	BC is stationary



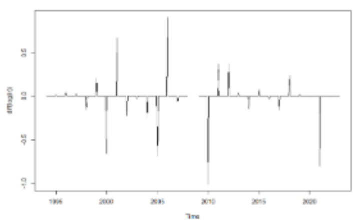
(a) KLSE



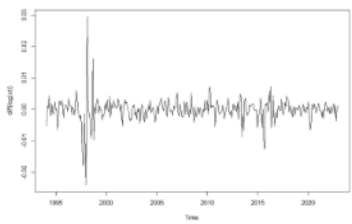
(b) CPI



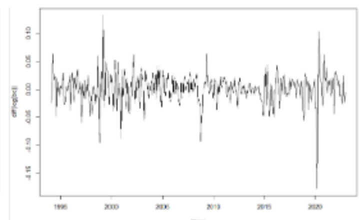
(c) GDP



(d) IR



(e) CR



(f) BC

Figure 2: Plot of the first difference of the variables

Ordinary Least Squared (OLS) Output

OLS estimates the parameters of a given regression model by minimising the sum of squared residuals between the observed values and the corresponding fitted values, creating a line between the data points. Hence, the OLS used to estimate the regression model coefficients is as follows:

$$D\log(KLSE)_t = B_0 + B_1\,D\log(CPI)_t + B_2\,D\log(GDP)_t + B_3 D\log(IR)_t + B_4 D\log(CR)_t + B_5 D\log(BC)_t + \varepsilon_{it}, \tag{2}$$

where D is the first difference, and we log-transformed all variables. Table 5 tabulated the output of the OLS. It indicates that the macroeconomic variables impact the stock market prices. Since all the predictor variables and the predicted variable are log-transformed, the interpretation of OLS is that a percentage change in X corresponds to a 1% change in Y. For instance, a 1% change in CR causes KLSE to drop by 84%, and with a *p*-value of 0.00648 (< 5%), it reveals a significant relationship between CR and KLSE. A significant relationship is also reported between BC and KLSE with a *p*-value of 0.0000 (< 5%), which suggests that an increase in BC causes KLSE to rise by 8.9%.

Table 5: OLS test output

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					
					R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.288[a]	.083	.069	.0252334294	.083	6.168	5	342	<.001	1.783

a. Predictors: (Constant), DBC, DCPI, DCR, DGDP, DIR.
b. Dependent variable: DKLSE.

Coefficients[a]

Model	Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Correlations			Collinearity Statistics	
	B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
(Constant)	.001	.001		.406	.685					
DGDP	- .026	.094	- .016	- .280	.780	.047	-.015	-.015	.800	1.249
DCPI	- .019	.025	.144	- .756	.450	-.045	-.041	-.039	.756	1.323
DIR	- .003	.015	- .045	- .227	.821	.018	-.012	-.012	.659	1.518
DCR	.842	.189	- .014	4.454	< .001	.248	.234	.231	.931	1.074
DBC	.089	.032	.144	2.747	.006	.157	.147	.142	.982	1.019

a. Dependent variable: DKLSE.

Residual Diagnostics

Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test examines the presence of serial correlation. The following hypotheses are used to assess the residuals for serial correlation in the OLS output:

H_0: There is no autocorrelation at any order $\leq p$

$H_{1:}$ There exists autocorrelation at some order $\leq p$

The test statistic follows a Chi-Square distribution with p degrees of freedom. Suppose the p-value that corresponds to this test statistic is less than a certain significance level (e.g., 0.05). In that case, we can reject the null hypothesis and conclude that autocorrelation exists among the residuals at some order less than or equal to p.

To verify further serial correlation, the Breusch-Godfrey test is a test for autocorrelation in the errors in a regression model. It uses the residuals from the model considered in a regression analysis, and a test statistic is derived from them. The null hypothesis is that no serial correlation of any order up to p. Table 6 outlines the serial correlation LM test. The p-value is 96.92%, higher than the 5% critical value. Thus, we do not reject the null hypothesis and infer no autocorrelation.

Table 6: Serial correlation LM test

Coefficients[a]											
Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	.000	.001		.126	.900					
	DGDP	- .004	.092	- .003	- .047	.963	- .001	- .003	- .003	.799	1.251
	DCPI	.002	.025	.004	.070	.944	.000	.004	.004	.755	1.324
	DIR	.001	.015	.005	.070	.944	.000	.004	.004	.657	1.521
	DCR	- .037	.192	- .011	- .194	.846	.006	- .011	- .010	.876	1.141
	DBC	- .004	.032	- .007	- .132	.895	.000	- .007	- .007	.976	1.024
	Residual_1	.109	.054	.110	2.031	.043	.116	.110	.110	.986	1.014
	Residual_2	.057	.056	.058	1.021	.308	.066	.055	.055	.915	1.093

a. Dependent variable: Unstandardised residual.

Heteroscedasticity Test

Heteroscedasticity refers to the variable variability varying over the range of values of the dependent variables that predict it. When the scatter of the dependent variable expands or shrinks as the price of the dependent variable rises, the scatterplot of those variables forms a cone-like shape (Moore *et al*., 2013). Meanwhile, the heteroscedasticity test tests the robustness of the OLS output, which is not reliable if heteroscedasticity exists. Using the logarithmic variables reduces the heteroscedasticity as it compresses the scale in which the variables are measured and mitigates correlations among them. In addition, this transformation reduces heteroscedasticity since the scale in which the variables are measured is compressed. Hence, the hypotheses are:

H_0: No heteroscedasticity.

H_1: Heteroscedasticity.

Table 7 summarises the results of the heteroscedasticity test, which indicates a *p*-value of 0.823, which is above the 5% critical value. Hence, we do not reject the null hypothesis.

Table 7: Heteroscedasticity test

ANOVA[a]						
	Model	Sum. of Squares	df	Mean Square	F	Sig.
1	Regression	.000	5	.000	.437	.823[b]
	Residual	.001	342	.000		
	Total	.001	347			

a. Dependent variable: SQRES.

b. Predictors: (Constant), DBC, DCPI, DCR, DGDP, DIR.

Normality Test

The Jarque-Bera normality test investigates the residuals for normality by testing whether the coefficient of skewness and excess kurtosis are jointly zero, presented as:

$$JB_{Test\ Statistic} = n\left[\frac{S^2}{6} + \frac{(K-33)^2}{24}\right]. \tag{3}$$

Based on the significant probability value, reject the null hypothesis if the *p*-value is less than 0.05 (5%) or *t*-value is larger than the critical value, whereas the error term is not normally distributed. The hypotheses are:

H_0: Residuals are normally distributed.

H_1: Residuals are not normally distributed.

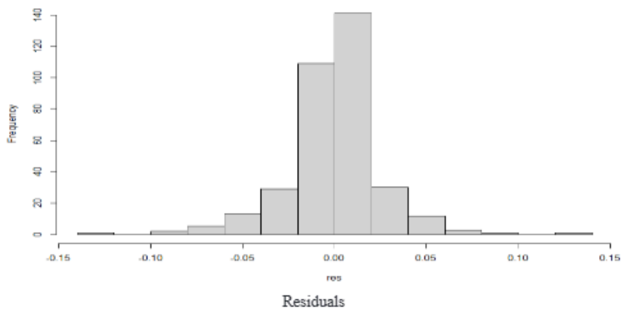


Figure 3: Histogram of residuals

Figure 3 indicates that residuals are not exactly normally distributed. The Jarque-Bera test confirms the non-normality of residuals, as the *p*-value of 2.2e-16 (very near to zero) is less than the critical value (5%). Thus, we reject the null hypothesis. Hence, the residuals are not normally distributed, as displayed in Figure 1, which suggests that the GDP increases constantly during the chosen period in this study. As opposed to the other variables, they exhibit occasional upward or downward fluctuations across the same period. Nevertheless, since a large sample size is used in this study, we used the *t*-test results. Hence, the diagnostic checking result reveals that the residuals from the linear regression are white noises. In line with this, the normality test indicates that the residuals are not normally distributed.

Granger Causality Test

The Granger Causality test is a statistical hypothesis test determining whether one time series predicts another. This test determines if historical values of one variable may predict changes in another (Granger, 1988). This test investigates the causal relationship between macroeconomic factors and the KLCI. In particular, the first difference of the four variables is made by applying the ADF test to obtain stationary variables to utilise the Granger Causality test. The hypotheses are:

H_0 : Y_t does not Granger cause $x_{t+1.}$.

H_i : Y_t does Granger cause x_{t+1}, at least one of the lags of Y is significant.

Table 8 indicates a unidirectional relationship between DGDP and DKLSE stock price since we reject the null hypothesis that DGDP does not Granger cause DKLSE. The *p*-value of 0.22% is less than the 5% critical value. This implies that the rate of GDP Granger causes stock price. Another one is that DCR does not Granger cause DKLSE. The *p*-value of 8.106e-07% is less than the critical value (5%), suggesting that CR Granger causes stock price.

Table 8: Test for Granger Causality between stock index and the macroeconomic variables

Null Hypothesis	*p*-Value	Results	Relationship
DGDP does not Granger cause DKLSE	0.002193*	Reject	Unidirectional relation
DKLSE does not Granger cause DGDP	0.33582	Do not reject	
DCPI does not Granger cause DKLSE	0.9958	Do not reject	No relation
DKLSE does not Granger cause DCPI	0.2169	Do not reject	
DIR does not Granger cause DKLSE	0.4824	Do not reject	No relation
DKLSE does not Granger cause DIR	0.381	Do not reject	
DCR does not Granger cause DKLSE	8.107e-07*	Reject	Unidirectional relation
DKLSE does not Granger cause DCR	0.4376	Do not reject	
DBC does not Granger cause DKLSE	0.1047	Do not reject	No relation
DKLSE does not Granger cause DBC	0.9439	Do not reject	

(*) means significant at a 5% critical level.

Scatterplot Matrix

A scatterplot matrix of the dependent variable against the other five independent variables is generated to determine the relationship between the variables (Figure 3). It suggests that the trendline in the scatterplot between some of the variables inclines upwards. This indicates a positive relationship exists between the KLSE index and the rate of GDPs and the price of BC, between CPI and CR, between the rate of GDPs and the price of BC, and between IR and CR. For all other relationships between variables, the slope inclined downwards, implying a negative relationship.

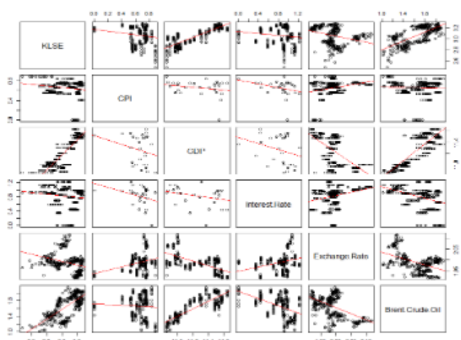


Figure 4: Scatterplot matrix

Correlation Coefficient

To determine the relationship between the factors affecting KLSE prices and the relationship with the index, we compute the correlation coefficient between two variables, x and y, as follows:

$$r_{xy} = \frac{cov(x,y)}{\sqrt{var(x)}\sqrt{var(y)}}, \tag{4}$$

where $0.1 < |r| < 0.3$ indicates weak correlation, $0.3 < |r| < 0.5$ indicates moderate correlation, and $0.5 < |r|$ indicates strong correlation.

In Table 9, the values of the correlations between the variables are documented. The correlation coefficients suggest a weak correlation between KLSE and CPI with -0.161 and between KLSE and IR with -0.138. Meanwhile, the correlation coefficient between KLSE and GDP and between KLSE and BC demonstrates a strong correlation with 0.862 and 0.716, respectively. At the same time, the correlation coefficient between KLSE and CR is -0.307, which indicates a moderate correlation.

Table 9: Correlation matrix

		KLSE	CPI	GDP	IR	CR	BC
KLSE	Pearson Correlation	1	- .161**	.862**	- .138**	- .307**	.716**
	Sig. (2-tailed)		.003	< .001	.010	< .001	< .001
	N	348	348	348	348	348	348
CPI	Pearson Correlation	- .161**	1	- .240**	- .320**	.283**	- .053
	Sig. (2-tailed)	.003		< .001	< .001	< .001	.320
	N	348	348	348	348	348	348
GDP	Pearson Correlation	.862**	- .240**	1	- .287**	- .629**	.854**
	Sig. (2-tailed)	< .001	<.001		< .001	< .001	< .001
	N	348	348	348	348	348	348
IR	Pearson Correlation	- .138**	- .320**	- .287**	1	.300**	- .436**
	Sig. (2-tailed)	.010	< .001	< .001		< .001	< .001
	N	348	348	348	348	348	348
CR	Pearson Correlation	- .307**	.283**	- .629**	.300**	1	- .469**
	Sig. (2-tailed)	< .001	< .001	< .001	< .001		< .001
	N	348	348	348	348	348	348
BC	Pearson Correlation	.716**	- .053	.854**	- .436**	- .469**	1
	Sig. (2-tailed)	< .001	.320	< .001	< .001	< .001	
	N	348	348	348	348	348	348

**. Correlation is significant at the 0.01 level (2-tailed).

Multicollinearity Tests

To identify multicollinearity, we use the Variance Inflation Factors (VIF) given as follows:

$$VIF = \frac{1}{1 - R^2{}_j}, \tag{5}$$

where R_j^2 is the coefficient of determination obtained when X_j is regressed on other X_{p-1} variables in the model. The VIF is the ratio of variance in a model with multiple terms, where it measures how much the variance of an estimated regression coefficient increases if the predictors are correlated. Note that the largest VIF value among all variables indicates multicollinearity. The interpretation of the VIF is as follows:

$VIF < 5$	No multicollinearity
$5 \leq VIF \leq 10$	Moderate multicollinearity
$VIF > 10$	Severe multicollinearity

We test the model's assumptions to detect model "lack of fit", violation of assumptions, the invalidity of the inferences, outliers, and influential observations. Hence, this confirms that the model meets the assumptions of the multiple regression model. Data transformation is performed prior to discarding any variables if the assumptions are unmet.

Table 5 also provides that via the multicollinearity test VIF, the explanatory variables are not collinear since the measurement of all the variables (1.249, 1.323, 1.518, 1.074, and 1.019, respectively) are less than 10. This explains why multicollinearity does not exist among all the explanatory variables considered in this study. Figure 4 displays the output for the residuals, and no obvious pattern in the SAC or SPAC ensures the results' robustness.

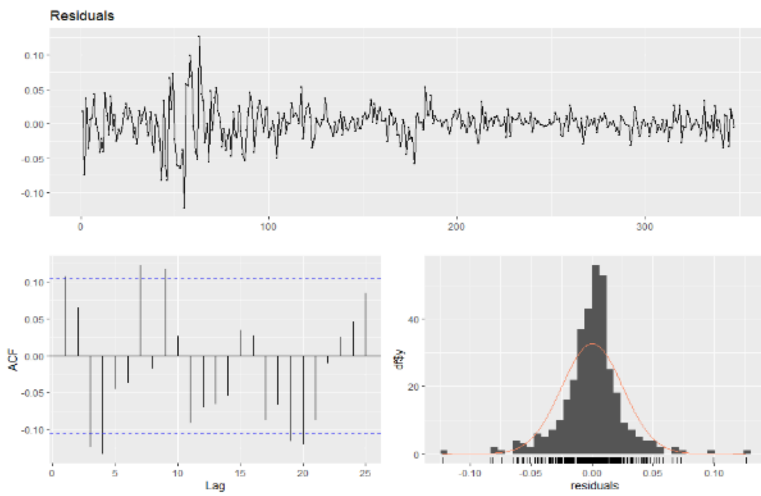


Figure 5: ACF plot of residuals

Model Selection

Stepwise Regression

Stepwise regression is one way to determine the best model from a regression study. The first step is to compute the correlation matrix between the dependent and independent variables. The first variable entry is the variable that has the highest correlation and is significant with the dependent variable. The second inbound variable is the variable that has the highest partial correlation and is still significant. After a certain variable enters the model, the other variables are assessed. If any variable is not significant, the variable is released.

The forward stepwise regression method is used in this study to determine the independent variables for a best-fit model, where the variables are considered one at a time in the linear regression model. As one new element is added to the model, its accuracy is verified to select the best model. The p-value denotes the chance that the null hypothesis is accurate, where the lower the p-value is, the more useful the factor. Consequently, the variables are added to an empty model one by one, from low to high *p*-values. This is repeated until there are no significant variables left to be added to the model.

Typically, multiple regression will display the variation explained by each predictor in the model simultaneously. Meanwhile, stepwise regression is used to add or remove each predictor from the model one at a time and observe how the variance explained R^2 changes. In other words, stepwise regression can evaluate the relative weights of each predictor and determine whether adding or removing certain variables significantly improves the model's predictive performance.

From Table 10, the "B" values are the coefficients for each variable. That is, they are the values by which the variable's data should be multiplied in the final linear equation we might use to predict. The "Constant" is the intercept equivalent in the equation. Hence, the best-fitted multiple linear regression equation is:

$$D\log(KLSE)_t = 0.001 + 0.837D\log(CR)_t + 0.087D\log(BC)_t + \varepsilon_{it}. \quad (6)$$

Equation (4) can be interpreted as follows: When the independent variables are zeros, the logarithmic price of the KLSE index is 0.001. When the CR is fixed, a unit increase in CR increases the logarithmic price by 0.837. On the other hand, when the BC futures are fixed, a unit increase in the CR increases the logarithmic price by 0.087.

The null hypothesis and alternative hypothesis of the test of significance on each model are different based on the number of variables in the regression model. An example of the null and alternative hypothesis of the test of significance on Model 2 is as follows:

$H_0 = B_4 = B_5 = 0$

$H_1 = \textit{at least one } B_j \neq 0,$

where j = 4,5. The *p*-value obtained for each model is 0.0000, smaller than 5%. Hence, we reject the null hypothesis. There is sufficient evidence to conclude that all the models are significant. In addition, roughly 8% of the variation in the dependent variable can be explained using the independent variables listed. This indicates that 8% of the variation of DKLSE is explained by the independent variables included in each model. Since a model with a higher R_2 value is preferable. Hence, we chose Model 2.

Overall, the Granger Causality test reveals that GDP and CR Granger cause the stock prices, while the stock price does not affect any macroeconomic variables. This result differs slightly from the stepwise regression result in Table 10. However, CR has the same element in both tests.

Table 10: Stepwise regression test

Variables Entered/Removed[a]			
Model	**Variables Entered**	**Variables Removed**	**Method**
1	DCR	.	Stepwise (Criteria: Probability-of-F-to-enter < = .050, Probability-of-F-to-remove > = .100).
2	DBC	.	Stepwise (Criteria: Probability-of-F-to-enter < = .050, Probability-of-F-to-remove > = .100).
a. Dependent variable: DKLSE			

Model Summary[c]				
Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**
1	.248[a]	.061	.059	.0253781304
2	.284[b]	.081	.076	.0251490731

a. Predictors: (Constant), DCR

b. Predictors: (Constant), DCR, DBC

c. Dependent variable: DKLSE

ANOVA[a]						
	Model	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
1	Regression	.015	1	.015	22.599	< .001[b]
	Regression	.019	346	.010		
	Total	.237	347			
2	Regression	0.19	2	0.10	15.172	<.001[c]
	Regression	.218	345	.001		
	Total	.237	347			

a. Dependent variable: DKLSE

b. Predictors: (Constant), DCR

c. Predictors: (Constant), DCR, DBC

Coefficients[a]								
Model		**Unstandardised Coefficients**		**Standardised Coefficients**	**t**	**Sig.**	**Collinearity Statistics**	
		B	**Std. Error**	**Beta**			**Tolerance**	**VIF**
1	(Constant)	.001	.001		.523	.601		
	DCR	.872	.183	.248	4.754	< .001	1.000	1.000
2	(Constant)	.001	.001		.377	.707		
	DCR	.837	.182	.238	4.594	< .001	.995	1.005
	DBC	.087	.032	.140	2.708	.007	.995	1.005

a. Dependent variable: DKLSE

Confidence Interval

The (1-α) 100% confidence interval for β_j is also calculated using:

$$b_j \pm t_{\frac{\alpha}{2},n-k-1}\, s(b_j), \tag{7}$$

where $t = \frac{b_j}{s(b_j)}$. The confidence intervals for each B_i in Model 2 is a 95% confidence interval for B_0 = [-0.002, 0.003] , 95% confidence interval for B_4 = [0.479, 1.1196] , and a 95% confidence interval for B_5 = [0.024, 0.149].

Table 11: Summary of the confidence interval of the model at 95% level

Coefficients[a]											
Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	.001	.001		.523	.601	- .002	.003		
	DCR	.872	.183	.248	4.754	< .001	.511	1.233	1.000	1.000
2	(Constant)	.001	.001		.377	.707	- .002	.003		
	DCR	.837	.182	.238	4.594	< .001	.479	1.196	.995	1.005
	DBC	.087	.032	.140	2.708	.007	.024	.149	.995	1.005
a. Dependent variable: DKLSE										

Model Specification

The final predictive model equation is constructed using the parameters and variables chosen after filtering according to the model assumptions and the model adequacy tests by removing all the variables that have negative effects on the model that are insignificant. Moreover, we used Root Mean Square Error (RMSE) to measure the differences between values predicted by the model and observed values.

The model suggested to fit the data accurately is ARIMA (0,0,9) since the stationary R^2 value of 0.112 is good. Additionally, RMSE of 0.025, MAPE of 159.36, and MAE of 0.017 indicate a better fit.

Table 12: Model specification for Granger Causality test

Model Description				
			Model Type	
Model ID	DKLSE	Model_1	ARIMA (0,0,9)	
Fit Statistic		Mean	Minimum	Maximum
Stationary R-squared		.112	.112	.112
R-squared		.112	.112	.112
RMSE		.025	.025	.025
MAPE		159.366	159.366	159.366
MaxAPE		3406.173	3406.173	3406.173
MAE		.017	.017	.017
MaxAE		.127	.127	.127
Normalised BIC		-7.331	-7.331	-7.331

Model Statistics						
Model	Number of Predictors	Model Fit Statistics	Ljung-Box Q (18)			Number of Outliers
		Stationary R-squared	Statistics	DF	Sig.	
DKLSE-Model_1	2	.112	26.994	16	.042	< .001

Conclusions

In this study, through forward stepwise regression in the OLS selection method using a multiple linear regression approach, we identify and examine a few macroeconomic factors that affect FTSE Bursa Malaysia KLCI, which are CPI, rate of GDP, IR, CR, and BC futures price. The linear regression test results reveal that the CR and BC prices against the KLCI are positively and significantly related. The other results demonstrate an insignificant relationship with the stock price.

This empirical study performs the necessary analysis to determine the factors affecting FTSE Bursa Malaysia KLCI using stepwise regression analysis and the Granger Causality test. For instance, the positive relationship between CR and stock price can be explained by the fact that when local currency depreciates, local companies become more competitive, increasing their exports to maintain their turnover. Moreover, as the currency weakens, companies whose earnings are export-based benefit since exported goods become cheaper, increasing their profits. Another positive relationship between stock price and BC futures may be due to responses to underlying shifts in global demand. Furthermore, the Granger Causality test suggests that only the rate of GDPs and CR cause the stock prices, while the stock prices do not affect any other macroeconomic variables. However, the Granger Causality is only for reference as it does not provide any insight into the relationship between the variables since it is not true causality, unlike "cause and effect" analysis.

From the analysis, we observed that only two of the five selected macroeconomic variables, namely CR and BC futures, are significant and may influence FTSE Bursa Malaysia KLCI. A model equation to fit specific macroeconomic factors within a fixed period for predicting the FTSE Bursa Malaysia KLCI is obtained. Model 2 is the best-fitted multiple linear regression. We managed to fit our predictors in a regression model and identify crucial variables that can successfully make predictions on FTSE Bursa Malaysia KLCI. The prediction is crucial for multiple purposes, such as investments and using other macroeconomic variables as indicators to indicate the downfall or rise of the stock market. Moreover, the outcome of this study may benefit investors by predicting the trend that the stock will follow within a fixed period due to previously predetermined factors. It can also be utilised as a policy tool to encourage overseas portfolio investments by stabilising the stock market.

Other than the five variables considered in this study, many other macroeconomic variables can be included in the multiple linear regression model to ensure that the accuracy and predicting power of the model will be higher and more applicable. Aside from macroeconomic conditions, various factors influence stock prices and movements, which can be found in microeconomic variables. Therefore, for future study, we may explore the significance of microeconomic factors in stock price movements and how an investor can reduce microeconomic risk by implementing a robust portfolio diversification plan. Furthermore, we may examine the impact of other elements using different methods or criteria to determine their significance and whether they influence the stock market or not.

Acknowledgements

The authors thank the reviewers for their comments on improving the manuscript's readability.

Conflict of Interest Statement

The authors declare that they have no conflict of interest.

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