Investigate the Effect of Macroeconomics Factor to Malaysian Stock MarketUsing Granger Causality Analysis

AzmeKhamis, Chan Man Seong, KekZhi Xuan, Goh Chin Hang, Wong WengHao, Aw Yew Chung

Department of Mathematics and StatisticsFaculty of Applied Science and Technology
UniversitiTun Hussein Onn Malaysia

IJASR 2021
VOLUME 4
ISSUE 4 JULY – AUGUST **ISSN: 2581-7876**

Abstract: Uncertainty in the movement for the Malaysian stock market was concluded to be influenced by the changes in several macroeconomic factors in which related to some relevant incidents. Therefore, it is meaningful to determine their effects on the Malaysian stock market in order to justify the changes in several macroeconomic factors This study determines how the causal relationship between the macroeconomic factors and the Malaysian stock marketing which starting from January 2014 until December 2019. The Malaysian stock market, crude oil, exchange rate and gold price are selected in this study.This is because of several macroeconomics factors are suspected to have significant effects on the uncertainty movement of the Malaysian stock market. In order to investigate the relationship between these selected macroeconomic variables and the Malaysian stock market, the Granger causality test isadopted. The findings showed that there is a long-run cointegration relationship exists among the macroeconomic factors and the Malaysian stock market.

Keywords: Granger Causality Analysis, Malaysian Stock Market, Cointegration

1. Introduction

The stock market is a union market where the buyers and sellers can stock simultaneously in business. It allows many people to do trading in public together by buying and selling in the market. Malaysia stock market or also known as Bursa Malaysia is one of the biggest stock markets in Southeast Asia. Malaysia stock market has undergone continuous growth from a small market until becoming one of the important stock markets in the global stock market for today and it is an important economic indicator for a country's economy. Financial Bursa Malaysia Kuala Lumpur Composite Indexalso known as FBMKLCI is represented by 30 main companies with one of six tradable indices in the series of Financial Time Stock Exchange (FTSE). Furthermore, Azevedo*et al.* (2014) stated that the Kuala Lumpur Composite Index (KLCI) was one of the best analyses to be referred by the Asia Pacific. In the study of Zhen, Choo & Muda (2013) also agreed that FBMKLCI is good to be used for representing Malaysia's stock market.

The stock market had been closely associated with the country's economic growth and also the effect of causal relationship between macroeconomic variables is one of the popular topics to be debated in the past few decades (Caporale, Howells &Soliman, 2004; Barakat*et al.* 2016). In the context of Malaysia, the stock market had a growth of 9.4% and a market capitalization growth of 14.4% annually(Teoh *et al.* 2018). Sujit& Kumar (2011) stated that any exchange rate change can cause an immediate effect on the price of some of the commodities such as oil and gold.The stock price and crude oil price are both strongly connected since the fluctuation of oil prices will directly influence the stock price through the effect on cash flow and discount rate. The effect of oil price on corporate cash flow is critical due to oil is an important source for the process of development and production. The stock price changes will be also directly affecting the decision to invest in the corporate which will be influencing the oil price(Miller &Ratti, 2009).

Preethi&Santhi (2012) defined the stock price as the company's stock from the public market which is known as the stock market. In Malaysia, the stock price group is known as Bursa Malaysia. Bursa Malaysia is playing an important role to evaluate the performance of 30 large companies (FTSE Russell, 2020). The stock price would faster the economic growth for less-developed countries and can be used as to measure the economic growth (Mun, Siong, & Thing, 2009; Caporale, Howells &Soliman, 2004; Kwon & Shin, 1999; Nordin, Nordin&Shahimi, 2016; Arestis&Demetriades, 1997; Tuyon& Ahmad, 2016).Many researchers has been embarked and studied on modelling and forecasting Malaysian stock price such as Kin, Hasan &Hamdan (2017), Azevedo*et al.* (2014) Ying, Zakaria,

&Mutalib (2017) (Hasan*et al.*, 2016), Siddhivinayak&Imad (2009, Kulkarni &Haidar (2009), Aloui, Nguyen, and Njeh (2012) and Nordin, Nordin&Ismail (2014). Study on the causality relationship between stock price and other factors has been carried out, such as oil and gas industry (Razak, Hadi, Yap, & Iqbal, 2014), crude oil prices (Dhaoui and Khraief, 2018; Ahmed&Wadud, 2014), and also gold price (Bandyopadhyay, 2016; Tripathy&Tripathy, 2016; Hatamlou, 2019 and Hafezi*et al.*2018).

The data used to examine the cointegration and causal relationship between macroeconomic factors and the stock market was collected. Malaysian Stock Market is defined as which comprises of 30 largest companies from the main market in Bursa Malaysia, represent the Malaysian stock market performance more aptly. The data collected for this study are secondary data. It is a set of monthly time series data from January 2014 until December 2019. All of the data downloaded from Yahoo Finance (https://finance.yahoo.com/). The variables used to measure the microeconomic factors are Malaysian Stock Market (KLCI), Crude OilPrice (CPO), Exchange rate (ER) and Gold Price (GP). Therefore, this study is carried out to investigate the causal relationship among the factors as can be used to forecast Malaysian stock price.

2. Research Methodology

2.1 Granger Causality

Granger causality developed in the field of econometric time series analysis and also applied in various application fields. **G**ranger causality is a statistical tool developed to analyse the flow of information between time series. Neuroscientistshave applied Granger causality methods to diverse sourcesof data, including electroencephalography (EEG), magnetoencephalography(MEG), functional magnetic resonance imaging(fMRI), and local field potentials (LFP). (Stokesa&Purdonb, 2018).

Granger (1969) formulated a statistical definition of causality based on the premises that (*i*) a cause occurs before its effect and (*ii*) knowledge of a cause improves prediction of its effect. Under this framework, a time series ($x_{i,t}$) is Granger causal of another time series ($x_{j,t}$) if inclusion of the history of x_i improves prediction of x_j over knowledge of the history of x_j alone. Specifically, this is quantified by comparing the prediction error variances of the one-step linear predictor, $\hat{x}_{j,t}$, under two different conditions: one where the full histories of all-time series are used for prediction and another where the putatively causal time series is omitted from the set of predictive time series. Thus, ($x_{i,t}$) Granger causes ($x_{j,t}$) if

$$var\left(x_{j,t} - \hat{x}_{j,t}|x_{j,0:t-1}\right) > var\left(x_{j,t} - \hat{x}_{j,t}|x_{j,0:t-1}, x_{i,0:t-1}\right)$$

Granger causality can be generalized to multistep predictions, higher-order moments of the prediction distributions, and alternative predictors (Lutkepohl, 2005; Barnett, Barrett & Seth, 2009)

In practice, the above linear predictors are limited to finite-order VAR models, and Granger causality is assessed by comparing the prediction error variances from separate VAR models, with one model including all components of the vector time series data, which we term the full model, and a second one including only a subset of the components, which we term the reduced model. To investigate the causality from ($x_{i,t}$) to ($x_{j,t}$), let

$$\begin{bmatrix} x_{j,t} \\ x_{i,t} \end{bmatrix} = \sum_{p=1}^{P} \begin{bmatrix} A_{j,j}^{f}(p) & A_{j,i}^{f}(p) \\ A_{i,j}^{f}(p) & A_{i,i}^{f}(p) \end{bmatrix} \begin{bmatrix} x_{j,t-p} \\ x_{i,t-p} \end{bmatrix} + \begin{bmatrix} \omega_{j,t}^{f} \\ \omega_{i,t}^{f} \end{bmatrix}$$

be the full VAR(P) model of all time series components, where the superscript ff is used to denote the full model.This model may be written more compactly as $x_t = \sum_{p=1}^{P} A^f(p)x_{t-p} + \omega_t^f$. The noise processes $\left(\omega_{j,t}^{f}\right)$ and $(\omega_{i,t}^{f})$are zero mean and temporally uncorrelated with covariance$E\left[\omega_{t1}^{f}\left(\omega_{t2}^{f}\right)^T\right] = \Sigma^f \delta_{t1-t2}$.Thus, the full one-step predictor of $x_{j,t}$ in the above causality definitionis $\hat{x}_{j,t}^{f} \sum_{p=1}^{P} \sum_{m\in(i,j)} A_{j,m}^{f}(p)x_{m,t-p}$. Similarly, let$x_{j,t} = \sum_{p=1}^{P} A^{r(i)}(p)x_{j,t-p} + \omega_{j,t}^{r(i)}$be the reduced VAR(P) model of the x_j (putative effect) components of the time series, omitting the x_i (putative cause) components. We use the superscript *r(i)*to denote this reduced model formed by omitting x_i. The noise process$\omega_{j,t}^{r(i)}$ is zero mean and temporally uncorrelated with covariance$\Sigma^{r(i)}$. The reduced one-step predictor of $x_{j,t}$ is thus $\hat{x}_{j,t}^{r(i)} = \sum_{p=1}^{P} A^{r(i)}(p)x_{j,t-p}$

2.2 Johansen's Test

There are two types of Johansen's test: one uses trace (from linear algebra), the other a maximum eigenvalue approach (Gonzalo & Lee, 1998; Engle & Granger, 1991). Both forms of the test will determine if cointegration is present. The null hypothesis for both forms of test is that there are no cointegrating equations. The difference is in the alternate hypothesis: the trace test alternate hypothesis is simply that the number of cointegrating relationships is at least one (shown by the number of linear combinations). The maximum eigenvalue test has an alternate hypothesis of $K_0 + 1$ (instead of $K>K_0$). Rejecting the null hypothesis in this situation is basically stating there is only one combination of the non-stationary variables that gives a stationary process (Wassell& Saunders, 2008; Wee & Tan, 1997).

3. Results and Analysis

3.1 Data Visualization

Data visualization is a graphical representation of information and data. By using visual elements like charts and graphs, data visualization tools provide an accessible way to see and understand trends, outliers, and patterns in data. In this study, graphical analysis and autocorrelation function (ACF) plot were applied. Graphical analysis is done by creating graphs to observe the trend and pattern of the data. Meanwhile, the ACF plot is used to examine the stationarity of data by looking at how well the present value of the series is related to its past values.

Figure 1:Time series plot for gold price

Based on the time series graphs (Figure 1), it can be concluded that there is a trend and no seasonality can be seen in these four macroeconomic factors. It means that all the variables are not stationary. As a result, the plot of ACF was then carried out to further identify the data stationarity.

3.2 Autocorrelation Function (ACF) Plots

In the ACF plot, we can observe when the values tend to degrade to 0 quickly, the time series can be concluded in a stationary condition. Meanwhile, a slow degradation indicates that non-stationary conditions. Figures 2 shows the ACF plots for all the variables.

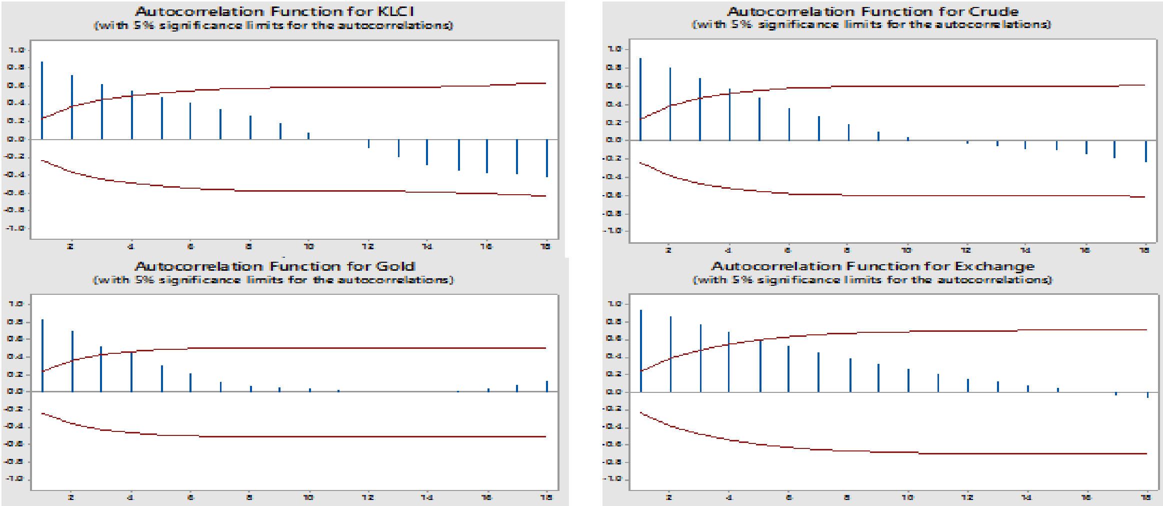

Figure 2: Autocorrelation Plot

3.3 Data Transformation and Differencing

As the data set is not stationary, all the variables are transformed into their natural logarithms to stabilize the variance and reduce the skewness of distribution for further analysis. The first differencing is carried out to remove the trend. Based on the ACF plots in Figure 3, it can be observed that the trend of all the variables are removed after applying logarithm and first differencing. However, there is a key procedure to study for non-stationarity, which is to test the existence of unit root instead of observing the graph. The unit root test is implemented to test the stationarity of the variables after transforming and differencing the data.

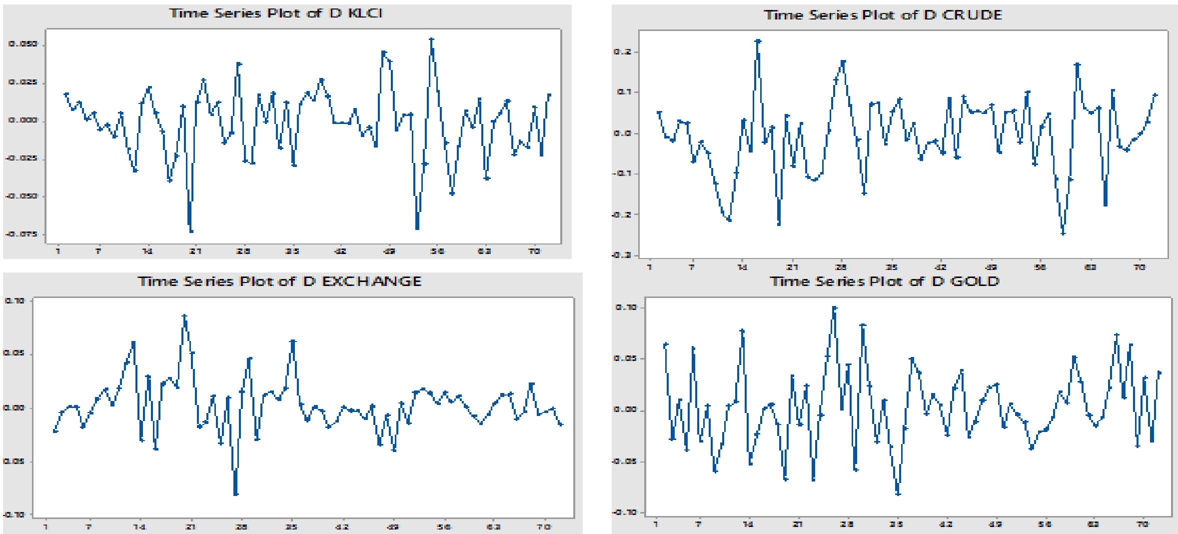

Figure 3: Data transformation and differencing plot

3.4 Unit Root Test

ADF test is first employed to test the stationarity of the four macroeconomic factors such as KLCI, crude oil, exchange rate, and gold price. While the table below shows the null hypothesis indicates the variable is not stationary as it contains a unit root. Meanwhile, the alternative hypothesis is the variable is stationary as it does not contain a unit root. The Table 1 reports the results of rejection or acceptance on the null hypothesis of the ADF test for the level and first difference form of the variables.Value-based on MacKinnon (1996) one-sided *p*-values. The value outside the parenthesis is the *t*-statistic. Value in parenthesis refers to the *p*-value. Asterisk (*) denotes the rejection of the null hypothesis of non-stationary at a 5% significance level.

Table 1: ADF Test at Levels and First Difference Form

Variables	ADF			
	Level		First Difference	
KLCI	-1.5367(0.764)	Accept H_0	-4.3158(0.01)	Reject H_0*
CRUDE OIL (CO)	-2.5346(0.3576)	Accept H_0	-4.262(0.01)	Reject H_0*
EXCHANGE RATE (ECR)	-1.9665(0.589)	Accept H_0	-4.1295(0.01)	Reject H_0*
GOLD PRICE (GP)	-2.243(0.4762)	Accept H_0	-3.9943(0.015)	Reject H_0*

Table 1 showed the results of the ADF unit root test in which the individual lag is chosen based on AIC and the test is conducted with a model of trend and intercept. In level form, it can be seen that all the variables accepted the null hypothesis since all the variables' *p*-value is larger than the significant level of 5%. The result indicates that there present a unit root exits and all the variables possess non-stationary at level form. After the first differencing, all of the four macroeconomic variables rejected the null hypothesis. This is because *p*-valuesof KLCI, crude oil, exchange rate, and gold price are smaller than the significant level of 5% which results in rejected the null hypothesis which representing the no unit root is still exists. In summary, it can be claimed that KLCI, crude oil, exchange rate and gold price have a high probability in a long-term association exists among the variables.

3.5 Number of Lags Selection

The optimum lag length is identified by estimating the order of the VAR model. Normally, annual data will adopt lags of 1 or 2, quarterly data use 1 to 8 lags while monthly data will use 6, 12, or 24 lags. However, there is no thumb rule on the choice of lag length. Lag length is used to ensure the result's reliability. Based on the test results, AIC and SIC recommend the order of 1. For this reason, 1 lag is chosen that will be appropriate due to the amount of sample data in this study.

3.6 Johansen Cointegration Test

From the selection of optimal lag number and order of 1 will be chosen so the test of Johansen cointegration is employed. The trace test and maximum eigenvalue test are used to identify whether the presence of a cointegration relationship between the variables. Since the optimal order of lags selection in AIC and SIC recommend an order of 1 so it defined as these four variables do not have any long-run cointegration relationship between the variables. As a result, the data analysis will proceed to estimate the vector autoregressive (VAR) model.

3.7 Vector Autoregression (VAR) Model

The vector autoregression (VAR) model is one of the most successful, flexible, and easy to use models for the analysis of multivariate time series. It is a natural extension of the univariate autoregressive model to a dynamic multivariate time series. The VAR model has proven to be especially useful for describing the dynamic behaviour of economic and financial time series and for forecasting. The relationship between the Malaysian Stock Market and macroeconomic factors are displayed in the equation (1):

$$logKLCI = -0.002+0.106logKLCI_{t-1}+0.017logCO_{t-1}+0.162logECRe_{t-1}+0.064logGP_{t-1} \quad (1)$$

Based on the equation above, all macroeconomic factors and the Malaysian Stock Market itself having a relationship with the Malaysian Stock Market. When there is a 1% increase in the Malaysian Stock Market in the previous month, the stock market would increase by 0.11%. When there is a 1% increase on crude oil prices in the previous month, the Malaysian Stock Market would increase by 0.02%. If the exchange rate of the currency is increasing 1% would impact an increase on 0.16% to Malaysian Stock Market. Lastly, a 1% increase on gold price in the previous month would increase 0.06% of the Malaysian Stock Market.

The relationship between crude oil price with all macroeconomic factors and the Malaysian Stock Market was displayed in the equation (2):

$$logCO = -0.005+0.783logKLCI_{t-1} + 0.198CO_{t-1}+0.265logECR_{t-1}+0.033GP_{t-1} \quad (2)$$

Based on the equation above, all macroeconomic factors and the Malaysian Stock Market having a positive relationship with crude oil. When there is a 1% increase in the Malaysian Stock Market in the previous month would increase 0.78% crude oil price. Then, if there is a 1% increase on the crude oil price in the previous month the price in this month would increase by 0.2%. The exchange rate would have the highest effect on the crude oil price in which a 1% increase on the exchange rate in the previous month would increase 0.26% of crude oil price. Lastly, 1% change in gold price would increase 0.03% of crude oil price.

The vector autoregression model in equation (3) the relationship between the exchange rate in Malaysia with all microeconomic factors and the Malaysian Stock Market.

$$logECR=0.003-0.285logKLCI_{t-1}-0.034logCO_{t-1}-0.113logECR_{t-1}-0.157logGP_{t-1} \quad (3)$$

Based on the equation above, all macroeconomic factors and the Malaysian Stock Market having a negative relationship to the exchange rate. When there is a 1% increase in the Malaysian Stock Market in the previous month then the exchange rate would decrease by 0.29%. Next, if the crude oil price increasesby 1% in the previous month then the exchange rate would decrease by 0.03%. When the exchange rate in the previous month is increasedby 1% then the rate in this month would decrease by 0.11%. Lastly, the gold price has the most negative influence on the exchange rate in which when a 1% increase on gold price in the previous month would decrease 0.16% of the exchange rate.

The relationship between gold price with all macroeconomic factors and the Malaysian Stock Market was displayed in the equation (4):

$$logGP=0.002-0.219logKLCI_{t-1}-0.118logCO_{t-1}-0.434logECR_{t-1}-0.094GP_{t-1} \quad (4)$$

Based on the equation above, the model explains that when there is a 1% change in the Malaysian Stock Market in the previous month, the gold price would decrease by 0.22%. Next, 1% change in crude oil price in the previous month would decrease by 0.12% on gold prices in Malaysia. The exchange rate has the most negative influence on the gold price in Malaysia, if there is a 1% change on the exchange rate in the previous month, then the gold price would decrease 0.43%. Lastly, when there is a 1% change on gold price in the previous month, then the price in this month would decrease by 0.09%.

3.8 Granger Causality Test

Granger causality test is applied to determine the direction of causality relationship after estimating the long-run and short-run relationship among the variables. Figure 4 below showed a summary of the causality relationship for all variables' direction.Based on Figure 4, there is a unidirectional causality where KLCI and exchange rate granger cause crude oil respectively. It means that only the KLCI and exchange rate can influence crude oil. Besides that, KLCI and exchange rate granger cause gold prices. It means that when there is a change in KLCI or exchange rate, the gold price will be affected as the stock market leads the gold price.

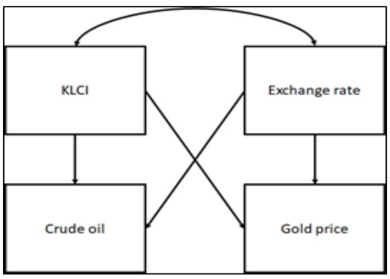

Figure 4: Causality relationship among the variables

Furthermore, a numerous unidirectional causality relationship was found among the factors such as KLCI granger cause crude oil, exchange rate granger cause crude oil, KLCI granger cause gold price and exchange rate granger cause gold price. On top of that, there is a bidirectional granger causality relationship between KLCI and the exchange rate. This indicates that when there is a change in KLCI or exchange rate, both the macroeconomic variables will be affected. Therefore, the result concluded that the macroeconomic factor exists granger between each other.

4.Conclusions

The causal relationship between the macroeconomic factors and the Malaysian stock market was identified using the Granger causality tests. This study revealed that there is a relationship between the Malaysian stock market and the exchange rate, gold price, and crude oil macroeconomic factors. The Malaysian stock market is positively affected by all the macroeconomics factors which are crude oil, exchange rate and gold price. Meanwhile, crude oil has a positive effect by the Malaysian stock market, exchange rate and gold price. However, the exchange rate is negatively affected by the Malaysian stock market, crude oil, and gold price. Besides, the gold price is negatively affected by the Malaysian stock market, crude oil, and exchange rate.

Based on the results of the granger causality test, there is a unidirectional causality where crude oil and gold prices are caused by the Malaysian stock market and exchange rate granger, respectively. This means that only the Malaysian stock and exchange rate can influence the price of crude oil and gold respectively. On the other hand, the granger causality relationship between the Malaysian stock market and the exchange rate is bidirectional. When the Malaysian stock market or exchange rate changes, both of the macroeconomic factors will be affected. Every macroeconomic factor adopted in this study, therefore, plays a vital role in the Malaysian stock market. This study showed that Malaysian stock markets are sensitive to macroeconomic changes.

It is recommended that future researchers include variance decomposition and impulse response function. The variance decomposition should be take into account to measure the percentage of variation forecast error which is explained for a better result by other variables.

5. References

1. Ahmed, R. A., &Shabri, A. B. (2014). Daily crude oil price forecasting model using arima, generalized autoregressive conditional heteroscedastic and Support Vector Machines.*American Journal of Applied Sciences*, *11*(3), pp. 425.
2. Aloui, C., Nguyen, D. K., &Njeh, H. (2012). Assessing the impacts of oil price fluctuations on stock returns in emerging markets. *Economic Modelling*, *29*(6), pp. 2686-2695.
3. Arestis, P., &Demetriades, P. (1997). Financial development and economic growth: assessing the evidence. *The economic journal*, *107*(442), pp. 783-799.
4. Azevedo, A., Karim, M., Gregoriou, A., & Rhodes, M. (2014). Stock Price and Volume Effects Associated with Changes in the Composition of the FTSE Bursa Malaysian KLCI. *Journal of International Financial Markets, Institutions and Money*, *28*, pp. 20-35.
5. Bandyopadhyay, G. (2016). Gold price forecasting using ARIMA model. *Journal of Advanced Management Science*, *4*(2), pp. 117-121.
6. Barnett L, Barrett A.B, Seth A.K (2009) Granger causality and transfer entropy are equivalent for Gaussian variables. *Phys Rev Lett* 103:238701.
7. Caporale, G. M., Howells, P. G., &Soliman, A. M. (2004). Stock market development and economic growth: The causal linkage. *Journal of economic development*, *29*(1), pp. 33-50.
8. Dhaoui, A., &Khraief, N. (2018). Empirical linkage between oil price and stock market returns and volatility: Evidence from international developed markets. *Economics Discussion Papers*, pp. 1-30.
9. Engle, R. F. and Granger, C. W. J. (1991). Long-run Economic Relationships: Readings in Cointegration, Oxford University Press.Johansen, S. "Statistical Analysis of Cointegrating Vectors." *Journal of Economic Dynamics andControl,* 12 (1988), 231-54.
10. FTSE Russell (2020). *FTSE Bursa Malaysia Index Series*. Retrieved from https://research.ftserussell.com/products/downloads/FTSE_Bursa_Malaysia_Index_Series.pdf
11. Gonzalo, J. & Lee, T. (1998). Pitfalls in testing for long run relationships. *Journal of Econometrics*. 86 (1998) 129—154.

12. Granger C.W.J. (1969) Investigation causal relations by econometric models and crossspectral methods. *Econometrica* 37:424–438.
13. Granger, C. W. J. (1981). Some properties of time series data and their use in econometric model specification. *Journal of Econometrics*, *16*, pp. 121-130.
14. Granger, C. W. J. & Weiss, A. A. (1983). Time Series Analysis of Error Correction Models. *Studies in Econometrics, Time Series and Multivariate Statistic*, pp. 255-278.
15. Hadi, A. R. A., Hussain, H. I., Zainudin, Z., &Rehan, R. (2019). Crude oil price and exchange rates - The case of Malaysia and Brunei. *International Journal of Financial Research*, *10*(5), pp. 1-10.
16. Hafezi, R., &Akhavan, A. N. (2018). Forecasting gold price changes : Application of an equipped Artificial Neural Network. *AUT Journal of Modeling and Simulation*, *50*(1), pp. 71-82.
17. Hasan, H., Chong, S. H., Ooi, W. T. & Ismail, M. T. (2016). Time series modelling on KLCI returns in Malaysia. *Reports on Economics and Finance*, *2*(1), pp. 69-81.
18. Hatamlou, A., &Deljavan, M. (2019). Forecasting gold price using data mining techniques by considering new factors.*Journal of AI and Data Mining*,*7*(3), pp. 411-420.
19. Kin, T. Y., Hasan, S. A., &Hamdan, N. (2017). Forecasting the financial times stock exchange Bursa Malaysia Kuala Lumpur composite index using geometric brownian motion. *Journal of Computing Research and Innovation*, *2*(1), pp. 45-49.
20. Kulkarni, S., &Haidar, I. (2009). Forecasting model for crude oil price using Artificial Neural Networks and commodity futures prices. *International Journal of Computer Science and Information Security*,*2*(1), pp. 1-8.
21. Kwon, C. S., & Shin, T. S. (1999). Cointegration and causality between macroeconomic variables and stock market returns. *Global Finance Journal*, *10*(1), pp. 71-81.
22. Lutkepohl H (2005). *New Introduction to Multiple Time Series Analysis* (Springer, Berlin).
23. Mun, H. W., Siong, E. C., & Thing, T. C. (2009). Stock market and economic growth in Malaysia: Causality test. *Asian Social Science*, *4*(4), pp. 86-92.
24. Nordin, S., Nordin, N., &Shahimi, W. R. M. A. (2016). Malaysian stock market: A spur to the country's economic growth. *China-USA Business Review*, *15*(2), pp. 55-61.
25. Preethi, G., &Santhi, B. (2012). Stock market forecasting techniques: A survey. *Journal of Theoretical and Applied Information Technology*, *46*(1), pp. 24-30.
26. Stokesa, P.A &Purdonb, P.L. (2018). Study of problems encountered in Granger causality analysis from a neuroscience perspective. *Proc Natl Acad. Sci.* USA 115(29). E7063–E7072).
27. Tripathy, N.&Tripathy, A. (2016). A study on dynamic relationship between gold price and stock market price in India. *European Journal of Economics, Finance and Administrative Sciences*, *88*, pp. 1-16.
28. Tuyon, J., & Ahmad, Z. (2016). Behavioural finance perspectives on Malaysian stock market efficiency. *Borsa Istanbul Review*,*6*(1), pp. 43-61.
29. Wassell, C. & Saunders, P. (2008). Time series evidence on social security and private saving: The issue Revisited. Retrieved March 31, 2020 from: http://www.cwu.edu/business/sites/cts.cwu.edu.business/files/Soc%20Sec%20Final%20Draft.pdf
30. Wee, P. & Tan, R. (1997). *Performance of Johansen's Cointegration Test.* In East Asian Economic Issues (Applied Economics Research Series) (v. 3).
31. Zhen, L. Z., Choo, Y., Muda, A. K., & Abraham, A. (2013). Forecasting FTSE Bursa Malaysia KLCI trend with Hybrid Particle Swarm Optimization and Support Vector Machine Technique. *2013 World Congress on Nature and Biologically Inspired Computing IEEE*, pp. 169-174.

