



Investment in Malaysia: Forecasting stock market using time series analysis

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> Stock market investment is an important and popular form of investment all across the world.

>Anyone who wishes to invest in the stock market would need to trade stocks in markets often called stock exchanges.

Companies which wish to list their shares in Malaysia can do so on the various board of the local stock exchange called Bursa Malaysia.

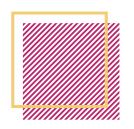




For the main board of Bursa Malaysia, a commonly used index is the Kuala Lumpur Composite Index (KLCI).

This index comprises of 30 largest companies on the Bursa's main board based on market capitalization.

The daily KLCI index will rise or fall based on the weighted daily price performance of these 30 largest stocks.





Fortunes and lost have been made in stock markets all over the world.

Therefore, it would be highly beneficial if one can forecast the performance of investments in companies listed on the stock market with a reasonable degree of accuracy.





There are several time series modeling techniques to obtain reliable forecasts of investments.

An important forecasting technique introduced in 1970 called Box and Jenkins is the Autoregressive Integrated Moving Average (ARIMA) model.

ARIMA model is good for short-term prediction (Li et.al, 2016 & Ayodeli et.al 2014).



Objectives



➤ To identify the most appropriate time series model for the KLCI

➤ To forecast the value of KLCI stock market for the coming three years

➤ To investigate whether investment in stock market is the best in terms of profit for the coming three years



Literature Review



| AUTHOR, YEAR | EXPLAINATION |
|--|--|
| J. Zhang and S. Li (2016) | The Shanghai Composite Index monthly closing price was collected from January 2005 until October 2016 and were used to build the ARIMA model. Forecasting for two months were carried out and compared with the actual value to investigate whether the ARIMA model fitted is adequate for the short-term Shanghai Stock Index prediction. The result shows the Shanghai Composite Index have a small rise in the last two months of 2016. |
| A. Ayodele, A. Aderemi and A. Charles (2014) | The researchers develop the ARIMA model based on the Nokia stock index from April 2005 to February 2011 with 3990 observations and Zenith Bank stock index from January 2006 to February 2011 with 1296 observations. The results revealed that the performance of the ARIMA model is quite good since the predicted values are fairly related to the actual value. |



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Literature Review



| AUTHOR, YEAR | EXPLAINATION |
|----------------------------------|---|
| Alkhazaleh and Hussein (2015) | Conducted a study on forecasting insurance sector volatility on the Amman Stock Exchange using ARIMA model. The researchers wished to predict the volatility on the Amman Stock Exchange using Box-Jenkins model. Weekly data of Amman Stock Exchange were accumulated using historical indices from January 2005 to April, 2010. In this study, the ARIMA model has shown its advantages in forecasting the stock market data. |







The model developed is known as ARMA model and defined as:

$$\begin{split} Y_t &= \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots \phi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \theta_q \varepsilon_{t-q} \\ (1 + \phi_1 B + \phi_2 B^2 + \cdots \phi_p B^p) Y_t &= \left(1 - \theta_1 B - \theta_2 B^2 - \theta_q B^q\right) \varepsilon_t \\ \phi_p(B) Y_t &= \theta_q(B) \varepsilon_t \end{split}$$





➤ However, for the case of non-stationary ARMA model, Box and Jenkins proposed the Autoregressive Integrated Moving Average.

The term (I) is integration referring as the differencing procedure with the notation *d* as the degree of differencing. The ARIMA model can be defined as:

$$\phi_p(B)(1-B)^d Y_t = \theta_q(B) \varepsilon_t$$





- > Four major steps involved in Box and Jenkins method:
 - -model identification
 - -parameter estimation
 - -model validation with diagnostic checking
 - -forecasting





- > Model identification involves:
 - -Logarithm transformation
 - -Autocorrelation Function (ACF)
 - -Partial Autocorrelation Function (PACF)
 - -Differencing
 - -Model selection based on the characteristic of the ACF and PACF.





Parameter estimation for the Box-Jenkins models is quite complicated, therefore, high quality software program that fits Box-Jenkins models is employed for the parameter estimation.

Main approaches to fitting Box-Jenkins models are non-linear least squares and maximum likelihood estimation.

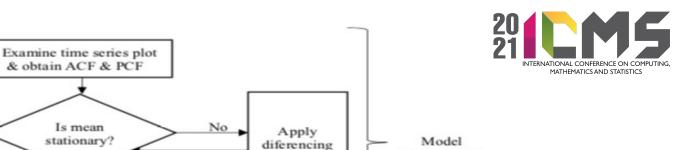
Model validation with diagnostic checking phase aimed to identify whether the estimated model is statistically adequate. The diagnostic checking is implemented based residuals.



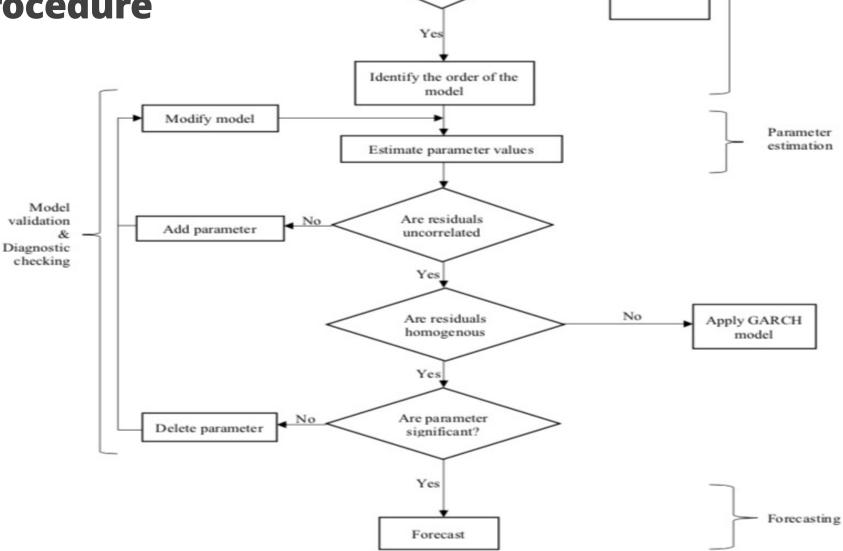


- Diagnostic checking involves:
 - -Residual analysis, ACF and PACF of the residuals,
 - -Breusch-Godfrey Lagrange- Multiplier test
 - -Heteroskedasticity test
 - -GARCH (Generalized ARCH) model
 - -Exponential GARCH (EGARCH) model
 - -GARCH-in-mean (GARCH-m) model
 - -Overfitting of the model
 - -Bayesian Information Criterion (BIC)
- Once the most adequate model is identified, forecasting can be generated

Flowchart Box & Jenkins modelling procedure



identification







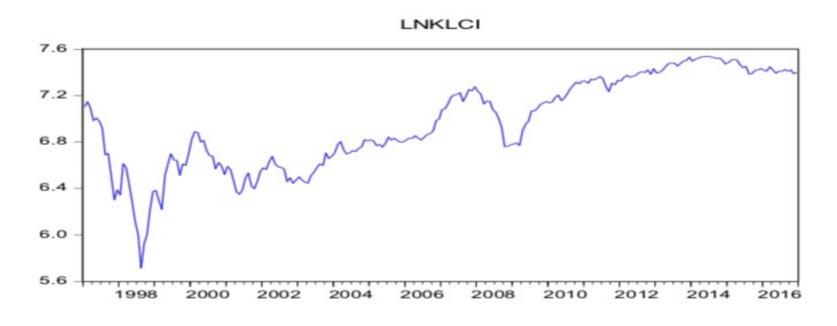
➤ Monthly data Kuala Lumpur Composite Index (KLCI) selected ranges from January 1997 to December 2018.

➤ Data fitted to an appropriate model and then the future KLCI return of investment from 2019 to 2021 is forecasted.

➤ KLCI is selected as the indicator due to its high accuracy to represent the Malaysian stock market performance as it comprises of thirty largest companies from the main market in Bursa Malaysia.







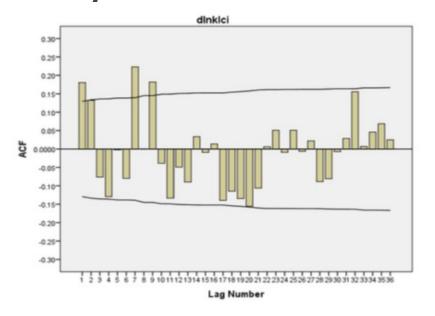
- Figure above shows time series plot of monthly KLCI from January 1997 to December 2016.
- > Decreasing trend from 1997, which is due to the Asian financial crisis.
- Then, positive increment for approximately 18 years.

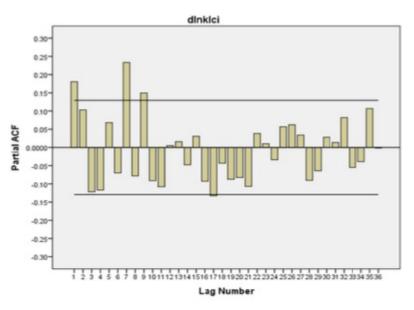


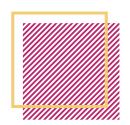


>The series is suspected to be non-stationary in mean.

Therefore differencing method is employed to obtain a stationary series.









- The model specification is determined based on the ACF and PACF of the differenced series.
- >The differenced series mean is now stationary.
- The application of GARCH model is done due to the time varying variance and heteroskedasticity was suspected to exist in the differenced.
- Three simplest time series models, AR (1), MA (1) and ARMA (1,1) are generated to determine the most appropriate model for the differenced series.







| Model | Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|------------|----------|-------------|------------|-------------|--------|
| AR (1) | C | 0.001049 | 0.005192 | 0.202095 | 0.8400 |
| | AR(1) | 0.180471 | 0.063975 | 2.820977 | 0.0052 |
| MA (1) | C | 0.001288 | 0.004864 | 0.264852 | 0.7914 |
| | MA(1) | 0.143708 | 0.064293 | 2.235198 | 0.0263 |
| ARMA (1,1) | C | 0.001110 | 0.005495 | 0.202096 | 0.8400 |
| | AR(1) | 0.377022 | 0.309850 | 1.216791 | 0.2249 |
| | MA(1) | -0.196744 | 0.327946 | -0.599928 | 0.5491 |

- The coefficients of AR (1) and MA (1) are significant at 5% significance level whereas the coefficients of ARMA (1,1) are not significant.
- ➤Only AR (1) and MA (1) model are considered as the candidate model.





- Next, diagnostic checking is implemented to validate the adequacy of the models.
- ➤ To verify the independence of the error term, serial correlation LM test is conducted.
- > Based on the results generated, the white noise assumptions are not fulfilled depicting the serial correlation still exist in the series.
- ➤ Overfitting is implemented to produce a better model which are AR (2), MA (2), ARMA (1,2), and ARMA (2,1) model.





- > Based on the overfitted models, only MA (2) has significant value of coefficients.
- Therefore, all models except MA (2) are discharged from further examination and diagnostic checking is performed once again.
- >ARCH-LM test was done whereby implied that the heteroskedasticity effect exists within the residuals.
- ➤ Thus, GARCH (1,1) is proposed to model the volatility of the data.
- Then overfitting was done again and another four new models are produced, which are MA (3)-GARCH (1,1), ARMA (1,2)-GARCH (1,1), MA (2)-GARCH (2,1), and MA (2)-GARCH (1,2).





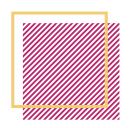


| Model | pth | qth | ARCH | GARCH |
|------------------------|-------------|-------------|------|-------|
| | coefficient | coefficient | | |
| MA (3)-GARCH (1,1) | - | NS | ** | ** |
| ARMA (1,2)-GARCH (1,1) | NS | * | ** | ** |
| MA (2)-GARCH (2,1) | - | * | * | * |
| MA (2)-GARCH (1,2) | - | NS | * | ** |

Footnote: NS-Not significant, *- significant at 10% level, **significant at 5% level

| Model | BIC |
|--------------------|---------|
| MA (2)-GARCH (1,1) | -3.1625 |
| MA (2)-GARCH (2,1) | -3.1462 |

Model with least BIC will be chosen as best adequate model acquired for the data which are MA (2)-GARCH (1,1).





Characteristic of the stock index has made it become hard to predict whereby the higher the risks the greater the uncertainties of leverage effect on the series.

Thus, MA (2) model is fitted with the EGARCH (1,1) model.

➤ EGARCH model captures the phenomena by assuming the impacts on the volatility asymmetrically.





Results of MA (2) model with EGACRH (1,1)

| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|--|--|--|--|--|
| MA(1) MA(2) | 0.059264 0.130362 | 0.072443 0.064164 | 0.818073 2.031686 | 0.4133 0.0422 |
| | Variance | Equation | | |
| C(3) C(4) C(5) C(6) | -0.329664 0.213895 -0.091701 0.974383 | 0.106780 0.064187 0.031354 0.013023 | -3.087310 3.332377 -2.924720 74.82141 | 0.0020 0.0009 0.0034 0.0000 |
| R-squared Adjusted R-squared S.E. of regression Sum squared resid | 0.039269 0.035216 0.065328 1.011460 | S.D. dependent var Akaike info criterion | | 0.001254 0.066510 -3.257190 -3.169915 |

- MA (2) component has become significant at 5% significance level, suggesting that MA (2) model is compatible with both GARCH and EGARCH model.
- The negative sign of the coefficient represents the existence of leverage effect on the series.
- This shows that KLCI will tends to have a bigger impact on the volatility in same magnitude.







The analysis is proceeded by investigating if the Capital Assets Pricing Model (CAPM) holds in the differenced series using the GARCH-m (1,1) model.

Results of MA (2) with GARCH-m

| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
|--------------------|-------------|--|-------------|-----------|
| @SQRT(GARCH) | 0.129456 | 0.083478 | 1.550788 | 0.1210 |
| MA(1) | 0.063849 | 0.074816 | 0.853423 | 0.3934 |
| MA(2) | 0.098443 | 0.068242 | 1.442565 | 0.1491 |
| | Variance | Equation | | |
| C | 3.96E-05 | 2.24E-05 | 1.771641 | 0.0765 |
| RESID(-1)^2 | 0.118975 | 0.035675 | 3.334930 | 0.0009 |
| GARCH(-1) | 0.856560 | 0.036957 | 23.17733 | 0.0000 |
| R-squared | 0.030238 | 0 S.D. dependent var 0.3 Akaike info criterion -3. | | 0.001254 |
| Adjusted R-squared | 0.022020 | | | 0.066510 |
| S.E. of regression | 0.065773 | | | -3.238461 |
| Sum squared resid | 1.020968 | | | -3.151186 |





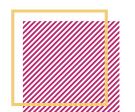
The positive sign of the risk -return parameter, @SQRT(GARCH) indicates there is a positive relationship between the risk and return.

- >This means higher risks will be compensated with higher return.
- ➤ However, since the coefficient of the parameter is not statistically significant at even 10% significance level, there is insufficient evidence to conclude there is a significant impact of volatility on the return.





- Since ARIMA (0,1,2)-GARCH (1,1) fulfilled the white noise assumption and selected as the most adequate model for the series, it is applied for the forecasting purpose.
- The predicted value of monthly KLCI from January 2017 to December 2018 is calculated and then are compared with the actual value to determine the accuracy of forecasted model.
- > The predicted value increase slightly in the first two months and remain constant until December 2018.
- ▶This situation are illogical since the stock market is always changing rapidly.
- ► However, the actual value still falls inside the predicted interval, indicating that this model still considered as reliable for forecasting.







| Date | Actual value | Predicted value | Lower prediction interval | Upper prediction interval |
|----------|--------------|-----------------|---------------------------|---------------------------|
| Jan 2017 | 1671.54 | 1637.870 | 1552.828 | 1722.912 |
| Feb 2017 | 1693.77 | 1640.546 | 1514.992 | 1766.099 |
| Mar 2017 | 1740.09 | 1640.546 | 1478.250 | 1802.841 |
| Apr 2017 | 1768.06 | 1640.546 | 1447.591 | 1833.500 |
| May 2017 | 1765.87 | 1640.546 | 1420.474 | 1860.617 |
| Jun 2017 | 1763.67 | 1640.546 | 1395.735 | 1885.357 |
| Jul 2017 | 1760.03 | 1640.546 | 1372.724 | 1908.366 |
| Aug 2017 | 1773.16 | 1640.546 | 1351.044 | 1930.047 |
| Sep 2017 | 1755.58 | 1640.546 | 1330.424 | 1950.667 |
| Oct 2017 | 1747.92 | 1640.546 | 1310.675 | 1970.416 |
| Nov 2017 | 1717.86 | 1640.546 | 1291.658 | 1989.433 |
| Dec 2017 | 1796.81 | 1640.546 | 1273.269 | 2007.823 |
| Jan 2018 | 1868.58 | 1640.546 | 1255.423 | 2025.668 |
| Feb 2018 | 1856.20 | 1640.546 | 1238.058 | 2043.034 |
| Mar 2018 | 1863.46 | 1640.546 | 1221.119 | 2059.972 |
| Apr 2018 | 1870.37 | 1640.546 | 1204.563 | 2076.528 |
| May 2018 | 1740.62 | 1640.546 | 1188.355 | 2092.736 |
| Jun 2018 | 1691.50 | 1640.546 | 1172.463 | 2108.628 |
| Jul 2018 | 1784.25 | 1640.546 | 1156.863 | 2124.228 |
| Aug 2018 | 1819.66 | 1640.546 | 1141.531 | 2139.560 |
| Sep 2018 | 1793.15 | 1640.546 | 1126.449 | 2154.642 |
| Oct 2018 | 1709.27 | 1640.546 | 1111.560 | 2169.492 |
| Nov 2018 | 1679.86 | 1640.546 | 1096.968 | 2184.123 |
| Dec 2018 | 1690.58 | 1640.546 | 1082.542 | 2198.549 |

Table beside shows comparison of actual value and predicted value of monthly KLCI from January 2017 to December 2018 with ARIMA (0,1,2)- GARCH (1,1).





| KLCI Stock Market | | |
|-------------------|---------------|--|
| Start: Jan 2019 | End: Dec 2021 | |
| 1690.609 | 1692.046 | |

- ➤ Based on the table above, the forecasted KLCI values for the coming three years only increase for one months, and subsequently remain constant value at index value 1692.046.
- ➤ The difference in value of only 1692.046 1690.609 = 1.437 indicates there is little increase in stock market index for the coming three years, close to no return for investment in stock market from 2019 to 2021, which is not realistic as stock market is known to be highly volatile and would not fix at one value.





| <i> </i> | |
|---|----------------|
| Segment of Period | Rate of Return |
| 1997-2000 | 0.559 |
| 2001-2003 | 1.091 |
| 2004-2006 | 1.339 |
| 2007-2009 | 1.070 |
| 2010-2012 | 1.341 |
| 2013-2015 | 1.040 |
| 2016-2018 | 1.014 |
| | |

- Thus an alternative method for forecasting of KLCI is proposed in Table above to make a better predicted value of KLCI.
- The table shows the investment on KLCI where investors had the highest loss from the period of 1997 to 2000 which is 44.1%. The highest rate of return per segment could goes up to 34.1 % whereas the lowest positive rate of return is 1.4 %.
- These phenomena indicating the stock market is highly volatile as the difference of profit is significantly higher or lower.





- Forecasting the value of KLCI stock market and investigating whether stock market is the best in terms of profit for three years to come are the main objectives of this study.
- ➤ Based on the findings, an appropriate time series model is determined for the KLCI series.
- The series is not stationary as it contains stochastic trend, but first differencing is sufficient to transform the series into a stationary series. In the end of the model selection, ARIMA (0,1,2) GARCH (1,1) model was the most adequate model obtained for the stock index.
- To validate the appropriateness of this model, in-sample forecasting was carried out by comparing the predicted value and actual value throughout the period of the beginning of 2017 to December 2018.





- However, due to forecast properties of ARIMA (0,1,2)-GARCH (1,1), where the MA component is significant, the forecasted values converge to a constant value. The results shown looks illogical but since the actual value falls inside the predicted interval, this model is still reliable in its forecast ability.
- However, the forecast values of KLCI series remain at a constant value suggest little to no increment for the future three years, also indicates there will be no profit in investing in the stock market.
- This is not realistic as stock market contains high volatility and the values should be fluctuating over time.





- ➤ Therefore, an alternative way is proposed such that the historical values of KLCI is segmented into several 3-years period and the return of investment is calculated.
- This aim is to provide a general picture to the investors about the return for investing in stock market for the next three years.
- The alternative method shows findings that the return rate of stock market has a highest loss of 44.1 % and a highest gain of 34.1%, which clearly express the risk of investing in stock market.
- Therefore, for an investor willing to take high risk, investment on KLCI stock market will be the suitable choice as its return might goes several times higher as well as lower.





- >As an alternative for the risk averse, fixed deposit is an option of investment.
- A Fixed Deposit (FD) is a special type of bank savings account where a higher rate of interest is earned provided the deposit, a fixed amount, is not withdrawn over a fixed period. Typical periods are one month, three months, six months and a year.
- > The interest is paid by the bank at the end of the stipulated period.
- Fixed deposit are popular in Malaysia because it is very safe and can earn better returns than an ordinary savings account. Fixed deposit rates are usually reference to a certain rates determined by Bank Negara Malaysia.
- In conclusion, time series analysis can be used although they have their limitations, for investigating the properties of the series and provide useful informations for investors to make prediction. It can also be used as a reference for investors for their investment plan.





21 THANK YOU

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