Menemui Matematik (Discovering Mathematics)
Vol. 43, No. 1: 9 – 20 (2021)

Crude Palm Oil Price Modelling: A Comparison of Time Series Model

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ABSTRACT

A variety of methods have been developed to model palm oil prices due to its rapid changes over time. The price modelling represents valuable and fundamental information to direct and indirect traders in fats and oils market. This study focuses on comparing the performances of two time series approaches which are the univariate and multivariate analysis in modeling the prices of palm oil. The univariate analysis produces Autoregressive Integrated Moving Average (ARIMA) while the multivariate analysis produces Autoregressive Distributed Lag (ARDL) model. This study uses monthly prices of crude palm oil as well as monthly production of crude palm oil, monthly closing stock of crude palm oil, monthly export and import of crude palm oil from January 2000 until December 2013. The findings show that production and export have positive impact on price while import and stock have negative impact on price of palm oil. This study implies that the government should reduce the import and closing stock of palm oil to upturn its price. For future recommendation, other factors that might affect the price of palm oil such as yield, and oil extraction rate should be integrated by other researcher.

Keywords: Palm oil, ARDL, ARIMA, cointegration, time series

INTRODUCTION

The commodity prices exhibit an increase after a decrease until the beginning of 21st century. The increase in prices has been led due to the increment of cereals and oil prices by 35% and 30% respectively. This volatility in agricultural commodities price affects the world food industry. Factors such as supply and demand as well as natural disaster and immediate change in policy decisions can affect each other as well as the price.

Most of developing countries rely on vegetable oils as a source of fat. In fact, vegetable oils primarily palm oil contribute major role in the global market of vegetable oils. This is due to their price which is cheaper prices (Ramli and Mohd Alias, 2006). Like any other agricultural commodities, palm oil also experienced price fluctuation.

The determination of agricultural commodities prices are based on a complex interaction among multiple factors including crude petroleum oil price, exchange rates, time-lag, demand and supply situation and slowing growth in agricultural productivity as well as the government policies. The palm oil industry in Malaysia is vulnerable to price fluctuations due to changes in the world economic forces such as fundamental factors of supply, demand and other technical and social factors (Mad Nasir et al., 1988).

Strong demand for oil palm products will lead to an increase in palm oil prices in the market. However, if the supply of palm oil growth is much faster than its demand, the prices will be negatively affected (Fatimah and Amna Awad, 2013). The low stocks or uncertainty about stock levels in some countries also causes price to increase drastically. Stocks can decrease when there is a response to a supply or demand changes. Nevertheless, new production is needed to increase the supply. The analysis of the effects of different macroeconomic variables is important since they can help policy makers of an economy to better formulate policies (Mohsen & Sujata, 2015).

A variety of methods have been developed to model palm oil price and they have been continuously refined up to the present. Utilizing the ARDL model by Amna et al. (2007) on the palm oil import demand in selected Middle East and North African (MENA) several countries shows that they can be represented by 10 single equation models. In fact, the study shows that the palm oil prices as well as the national income are significant determinants of palm oil demand across the 10 models. The prices of substitute oils in almost all countries have been found to play an important role in shaping the palm oil demand.

The study by Mad Nasir et al. (1988) to incorporate the stock variable into the model to examine its relationship with palm oil price concludes that the important determinants of palm oil prices are the stock levels, total consumption and world economic activity. Although Mad Nasir et al. (1988) conclude that crude oil contributes in palm oil price, a different study using the Bivariate Block Maxima and Bivariate Threshold Exceedances approach with a daily data suggest that rate of palm oil and crude oil prices has fairly weak dependence or even independence in extremes. In fact, the growth rate of palm oil and soybean oil prices has some dependence in extremes (Chuangchid et al., 2012).

The multivariate relationship between palm oil price, total area planted and production of Malaysian palm oil from 1972 to 2008 using Vector Error Correction Model concludes that the total area planted and palm oil price are negatively affected towards production of Malaysian palm oil (Fadli et al., 2011). In comparing performances of different forecasting models, Khin et al. (2013) employ three different models; Vector Error Correction Method (VECM), Multivariate Autoregressive Moving Average (MARMA) as well as ARIMA model. Using data from January 1980 to June 2011, the results revealed that MARMA model is more accurate and efficient in forecasting the price of palm oil.

Abdul Aziz et al. (2013a) compared two artificial intelligence approaches, namely artificial neural network (ANN) and adaptive neuro fuzzy inference system (ANFIS) in forecasting palm oil price using daily data from a period of January first, 2004 to the end of December 2011. The predictability power of the artificial intelligence approaches was also made in regard with the statistical forecasting approach such as the autoregressive fractionally integrated moving average (ARFIMA) model. The general findings demonstrated that the ANN model is superior compared to the ANFIS and ARFIMA models in predicting the palm oil prices. In the same year, Abdul Aziz et al. (2013b) compared the performance of ARFIMA model with ARIMA model. The conclusion from the study suggests that the usefulness of the ARFIMA model outperformed the existing ARIMA model.

Ayat et al. (2007) conducted a study on volatility between the domestic prices of selected palm oil products. From the analysis, it was found that palm oil has moderate price volatility. In fact, it is shown that palm oil is the price leader among the other selected palm oil products in the local market since palm oil is able to influence the prices of other similar products in both the short and long terms. A model was developed to forecast domestic prices for the selected palm oil products. The prices for crude palm oil and refined, bleached and deodorized (RBD) palm olein were forecast and found to be good with error of less than 2% with all the directions for prices correct.

Amna and Fatimah (2009) use Engle-Granger bivariate cointegration approach to investigate long-run relationship between price of crude oil and selected vegetable oils. The findings show that palm, rapeseed, soybean and sunflower oils were influenced by the price of petroleum price in the long run. On the other hand, Sabariah et al. (2014) concludes that the price of palm oil is positively significant in influencing the stock market index by using ARDL model.
Using historical variances of spot (the current price at which a particular can be bought or sold at a specified time and place) and futures price returns, a model for approximating palm oil prices for the spot-month and three-month contracts was developed and compared with the cost-of-carry model. The study concludes that inclusion of historical return variances in the form of the

convenience yield provides a better forecast of crude palm oil futures prices (Azmi and Shamsul, 2004).

The difference between cash and futures prices is known as basis. The risk factor associated with the physical commodity trade as well the local demand and supply situation can be obtained from this basis. The prediction of the cash price of palm oil can be obtained using forecast basis and future prices. A study by Ahmad Borhan et al. (2007) using basis from historical averages shows that the method is preferable compared to more complex forecasting models.

Meanwhile in using ordinary linear regression (OLS) method and time varying parameter model by Ramli and Mohd Alias (2006), the palm oil price is determined by the supply and demand factors, the price of substitute which in this case is soybean oil price. In fact, stocks of oils and fats and consumption of oils and fats are other variables that are included. However, these are not used directly but converted into a ratio called stock-usage ratio.

METHODOLOGY

This study models the price of palm oil prices using two approaches; the ARDL and ARIMA approach. This study uses monthly prices of crude palm oil as well as monthly production of crude palm oil, monthly closing stock of crude palm oil, monthly export and import of crude palm oil from January 2000 until December 2013.

Model 1: ARDL Model

ARDL model is an example of dynamic regression model. It allows the inclusion of other related variables in developing the model. There are five variables involved in this study. They are monthly price of crude palm oil (PRICE), monthly production of crude palm oil (PRO), monthly import volume of crude palm oil (IMPORT), monthly export volume of crude palm oil (EXPORT) and monthly closing stock of crude palm oil (STOCK). The monthly price of crude palm oil will become the dependent variable.

For economic analysis, many variables are used in logarithms (logs). In time series analysis this transformation is often considered to stabilize the variance of a series (Lütkepohl and Xu, 2012). Therefore, the ARDL model that will be used is

$$\begin{aligned}\ln PRICE_t = a_0 + \sum_{j=1}^{p1} f_j \ln PRICE_{t-j} + \sum_{j=0}^{p2} b_j \ln PRO_{t-j} + \sum_{j=0}^{p3} c_j \ln IMPORT_{t-j} \\ + \sum_{j=0}^{p4} d_j \ln EXPORT_{t-j} + \sum_{j=0}^{p5} e_j \ln STOCK_{t-j} + \varepsilon_t\end{aligned} \tag{1}$$

The above model assumes that the error term ε_t is serially uncorrelated.

ARDL Bound Test for Cointegration

The ARDL bound test for cointegration is applicable merely for either I(0) or I(1) process independent variables. However, the stationarity tests are necessary to avoid the inclusion of I(2) independent variables. The ARDL has numerous advantages. Unlike the most widely used method for testing cointegration which are the residual-based by Engle and Granger and maximum likelihood based by Johansen and Juselius tests, the ARDL approach can be applied regardless of the stationary properties of the variables in the samples and allows for inferences on long-run estimates, which is not possible under the alternative cointegration procedure.

In other words, this procedure can be applied irrespective of whether the series are I(0), I(1) or fractionally integrated. This avoids problems resulting from non-stationary time series data. Another advantage of this approach is that the model takes sufficient numbers of lags to capture the data generating process in a general-to-specific modelling framework. The ARDL method estimates $(p+1)^k$ number of regressions in order to obtain optimal lag-length for each variable, where p is the maximum lag to be used, and k is the number of variables in the equation.

Expressing ARDL Model as Error Correction Model (ECM)

The error correction model or ECM is an alternative class of models with a general form equivalent to the ARDL. The term error correction model applies to any statistical model that directly estimates the rate at which Y_t changes to return to equilibrium after a change in X_t. The parameters estimated are different but it is seen that they contain the same information so that the ECM representation is equally as general as the ARDL. The ECM does not need to be linked with cointegration and is appropriate for use with stationary data. The ECM integrates the short-run dynamics with the long-run equilibrium, without losing long-run information.

The unrestricted ECM representation of the ARDL models of our study is as follows :

$$\begin{aligned}\Delta \ln PRICE_t = a_0 &+ \sum_{j=1}^{p1} f_j \Delta \ln PRICE_{t-j} + \sum_{j=0}^{p2} b_j \Delta \ln PRO_{t-j} + \sum_{j=0}^{p3} c_j \Delta \ln IMPORT_{t-j} \\ &+ \sum_{j=0}^{p4} d_j \Delta \ln EXPORT_{t-j} + \sum_{j=0}^{p5} e_j \Delta \ln STOCK_{t-j} + g_1 \ln PRICE_{t-1} \\ &+ g_2 \ln PRO_{t-1} + g_3 \ln IMPORT_{t-1} + g_4 \ln EXPORT_{t-1} \\ &+ g_5 \ln STOCK_{t-1} + \varepsilon_t \end{aligned} \tag{2}$$

The above model is based on the assumption that the error term ε_t is serially uncorrelated. The terms with the summation signs in the above equations represents the error correction dynamics while the second part (terms with g_s) corresponds to the long-run relationship.

Choosing Lag Length on First Difference Variables

To determine the appropriate lag length p the ECM model (2) was estimated for p = 1 and 2 using OLS method. Then, the joint significant F-test of the lagged level variables in ECM model (2) ($\ln PRICE_{t-1}$, $\ln PRO_{t-1}$, $\ln STOCK_{t-1}$, $\ln IMPORT_{t-1}$ and $\ln EXPORT_{t-1}$) are used to test the presence of long run equilibrium relationship.

Pesaran et al. (2001) proposed the test based on standard F-statistics to test the significance of the lagged levels of the variables in a univariate equilibrium correction mechanism. Two sets of asymptotic critical values are provided: one when all regressors are purely I(1) and the other if they are all purely I(0). These two sets of critical values provide a band covering all possible classifications of the regressors into purely I(0), purely I(1) or mutually cointegrated.

The calculated F-statistics of the null hypothesis of no cointegration is compared with the critical value tabulated by Pesaran et al. (2001). All of the critical values in each case are categorize based on confidence interval sizes (0.100, 0.050, 0.025 and 0.010) for $k = 0,1,2, \dots 10$. This study uses Case III (unrestricted intercepts; no trends) since there are no trends involved in the equation and the intercepts have not been restricted. If the computed F-statistic falls above the upper bound critical value, the null hypothesis of no cointegration is rejected. Likewise, if the test statistic falls below a lower bound, then the null hypothesis cannot be rejected. Finally, if it falls inside the critical value band, the result would be inconclusive.

Estimation of ARDL model

Once cointegration is confirmed and the appropriate lag has been chosen, the ARDL can be estimated as well as the long-run relationship between the variables using the OLS method. The model can be selected using the model selected criteria such as adjusted R^2, Akaike Information Criteria (AIC) and Schwartz-Bayesian Criteria (SBC).

Model 2: Box-Jenkins ARIMA Model

Box and Jenkins in 1976 developed a practical procedure to analyze time series data that can be applied to non-seasonal and seasonal data. This study uses non-seasonal data.

Model Identification

To describe the model identification, consider the general ARIMA (*p*,*d*,*q*) process

$$\left(1 - \emptyset_1 B - \cdots - \emptyset_p B^p\right)(1 - B)^d y_t = \delta + (1 - \theta_1 B - \cdots - \theta_q B^q)a_t \quad (3)$$

Model identification refers to the methodology in identifying the required transformation and the orders of *p* and *q* for the model.

The first step to model identification is to plot time series data and choose appropriate transformation. Through the observation of the data plot, the idea whether the series contains seasonality, trend, nonconstant variance and stationarity of the data can be obtained.

The second step is to find the appropriate value of *d*. In other words, the differencing order or its stationarity need to be obtained. To test for stationarity, Augmented Dickey-Fuller (ADF) test can be used. When the original data is stationary, the value of *d* is zero. When the original data is not stationary, the value of *d* depends on how many differencing steps needed to ensure the data is stationary.

After the appropriate value of *d* has been identified, the third step is to compute and examine the sample autocorrelation function (ACF) and partial autocorrelation function (PACF) to identify the orders of *p* and *q*. ACF plot identifies the possible MA terms and PACF plot identifies the possible AR terms. If the data is AR(*p*), the ACF will decline steadily or follow damped sine wave and the PACF will cut off after lag *p*. If the data is MA(*q*), the ACF will cut off after lag *q* and PACF will decline steadily or follow damped sine wave.

Parameter Estimation

After model identification, the next step is to estimate the parameters of the models. Estimation of parameters can be done using several methods such as ordinary least square (OLS), maximum likelihood estimation, method of moments and iterative estimation. This study estimates the parameter through OLS approach.

Model Diagnostic

After the parameters have been estimated, we have to assess the adequacy of the model. This step is called model diagnostic. Model diagnostic is concerned with the goodness of fit test of a model. If the model does not fit well with the data, suggestion or selection of another model can be made. One of the useful diagnostic tests is portmanteau test.

Among portmanteau test are original Box-Pierce and modified Ljung-Box statistics. These portmanteau tests use all the sample of residual ACF, r. Under the null hypothesis, Box-Pierce test statistic and Ljung-Box test statistic are distributed as Chi-Square distribution, χ^2 with $(k - p - q)$ degrees of freedom. The model is inadequate if the *p*-value associated with the Q statistic is small (*p*-value < 0.05). This diagnostic will be used to test both ARDL and ARIMA model.

Stability Test

An additional test for ARDL model is stability test. Regression analysis of time series data is usually based on the assumption that the regression relationship is constant over time. In some applications, particularly in the social and economic fields, the validity of this assumption is open to question, and is often desirable to examine it critically, particularly if the model is to be used for forecasting.

This structural stability test proposed by Brown, Durbin and Evans (1975) is conducted by employing the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squares of recursive residuals (CUSUMSQ).

Model Evaluation

One of the primary objectives of time series analysis after model diagnostic is to estimate the values using the model that has been established. However, there are some criteria needed in order to choose the best model based on fitted values. Before starting to estimate the data, the best model has to be selected. This can be done with the help of model selection criteria; Akaike's Information Criterion (AIC) and Schwartz-Bayesian Criterion (SBC). By minimizing both terms in AIC and SBC, a model that is both parsimonious (does not overfit the data with too many parameters) was identified while also accurately modelling the data.

After the best model has been selected, its fitted accuracy criterion needs to be computed. Accuracy can be measured using measures such as Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). MAE is a type of accuracy quantity to measure how close the estimated values are to the eventual outcome. MAPE is a measure of accuracy of the estimated value in terms of percentage. It can be calculated as. The smaller the values of MAE and MSE, the better the model is.

RESULTS

This study uses five monthly data. The first data are monthly prices of crude palm oil in Malaysian Ringgit (MYR) per tonnes. The rest of the data are monthly production, import volume, export volume and closing stock of crude palm oil which are all in tonnes. All the data are from January 2000 until December 2013.

Model 1: ARDL Model

The stationary testing for each logarithmic variable is calculated to determine its integrating order. Table 1 shows the integrating order of all the logarithmic variables. Since none of the variables are I(2), therefore ARDL bound test is suitable for this analysis.

Table 1: Integrating Order of all the Logarithmic Variables

Variable	Order
Price	I(1)
Production	I(1)
Import	I(0)
Export	I(0)
Stock	I(0)

Existence of the Long-run Relationship

To test for the existence of the long-run relationship within the variables, the bound test procedure by Pesaran et al. (2001) is used. From the ECM model in (2), the bound test procedure suggest test the joint significant F-test of the lagged level variables in ECM model (2) ($\ln PRICE_{t-1}$, $\ln PRO_{t-1}$, $\ln STOCK_{t-1}$, $\ln IMPORT_{t-1}$ and $\ln EXPORT_{t-1}$) to test the presence of long run equilibrium relationship.

By imposing the lag, p =1 and 2, each model from each lag are tested for the joint significant F-test of the lagged level variables. The calculated F-statistics of the null hypothesis of no cointegration is compared with the critical value tabulated by Pesaran et al. (2001).
This study uses Case III (unrestricted intercepts; no trends) since there are no trends involved in the equation and the intercepts have not been restricted.

Since there are four regressor and it focuses on 5% critical value, the relevant critical value bounds are [2.86, 4.01]. The ECM model in (2) is estimated using p =1 and 2 with the calculated F-statistic are tabulated in Table 2.

Table 2: F-Statistics for Testing the Existence of a Long-Run Price Equation

Lag	F-statistics
1	2.7952
2	4.7233

At lag 2, the F-statistics are greater than the upper bound of critical value bounds (4.01). This suggests that there exists steady state equilibrium between these variables at lag 2. Therefore, choosing lag 2 is suitable for estimating ARDL model for the study.

Estimation of the ARDL model

After choosing the appropriate lag length ($p = 2$), equation (1) can be estimated with the help of Microfit software. Microfit will search through $(2+1)^5 = 243$ possible models. The best model was based on the model selection criterion selected by the user. This study uses AIC and SBC to select the best model.

ARDL model selected based on AIC

The ARDL model selected based on AIC is ARDL (2,2,0,0,2). Hence, the equation for ARDL (2,2,0,0,2) is :

$$\begin{aligned}\ln PRICE_t = {} & -0.52208 + 1.0677 \ln PRICE_{t-1} - 0.11178 \ln PRICE_{t-2} \\ & - 0.039538 \ln PRO_t + 0.0065773 \ln PRO_{t-1} \\ & + 0.16534 \ln PRO_{t-2} - 0.0037622 \ln IMPORT_t \\ & + 0.010531 \ln EXPORT_t - 0.14048 \ln STOCK_t \\ & - 0.14948 \ln STOCK_{t-1} + 0.21010 \ln STOCK_{t-2} + \varepsilon_t\end{aligned} \tag{4}$$

ARDL model selected based on SBC

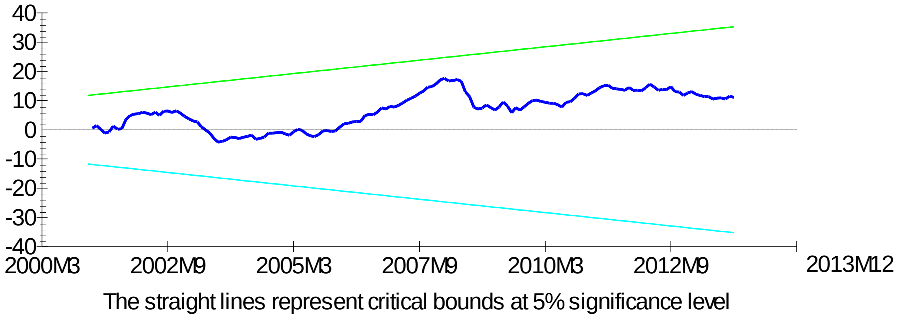
The ARDL model selected based on SBC is ARDL (1,2,0,0,2). Hence, the equation for ARDL (1,2,0,0,2) is :

$$\begin{aligned}\ln PRICE_t = {} & -0.25461 + 0.96508 \ln PRICE_{t-1} - 0.073284 \ln PRO_t \\ & + 0.012826 \ln PRO_{t-1} + 0.17474 \ln PRO_{t-2} \\ & - 0.0058371 \ln IMPORT_t + 0.014158 \ln EXPORT_t \\ & - 0.12753 \ln STOCK_t - 0.18205 \ln STOCK_{t-1} \\ & + 0.22217 \ln STOCK_{t-2} + \varepsilon_t\end{aligned} \tag{5}$$

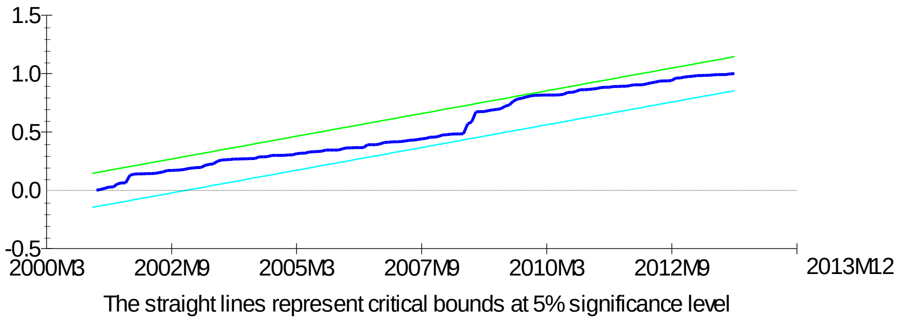
Model Diagnostics

After the parameters have been estimated, the adequacy of the model is tested using Ljung-Box statistics. This test uses all the sample of residual ACF of a fitted ARDL model, not the original series on whether the ARDL model has no autocorrelation. All the *p*-value associated with the Q statistic is large (*p*-value > 0.05). This implies that the null hypothesis of no autocorrelation cannot be rejected. Thus, this model is an adequate model and can be used to fit the data.

An additional test for ARDL model is stability test. This involved plotting the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squares of recursive residuals (CUSUMSQ) as depicted in Figures 1 and 2.



(a)



(b)

Figure 1: Plot for (a) CUSUM and (b) CUSUMQ of the recursive residual for ARDL (2,2,0,0,2)

The straight lines in both plots represent critical bounds at 5% significance level. Based from Figures 1 and 2, the plot of CUSUM and CUSUMSQ remains within the critical bounds. This means that the null hypothesis that all the coefficients and the ARDL are stable cannot be rejected.

Model 2: ARIMA model

The analysis also starts with stationary testing. ADF test will be used to test for stationarity. It is then followed by the process of model identification and parameter estimation. The ARIMA model obtained will then be used to estimate the value of palm oil price. For ARIMA model, the original data of price is used. ADF test on level price indicates that the first differencing level price will be used in the data analysis. After stationary testing has been done, the process of model identification is carried out.

Model Identification

In order to identify the model involved, the sample autocorrelation function (ACF) and partial autocorrelation function (PACF) need to be computed. For ARIMA models, the required model is ARIMA (p,d,q). By using PACF and ACF plots, the orders of p and q can be identified respectively. In ARIMA model, p is autoregressive (AR) order and q is moving average (MA) order. Since the first differencing of price is used, the differencing order, d for price data is $d = 1$.

There are 11 ARIMA models for price to be considered. Table 3 shows all the ARIMA models that are considered.

Table 3: Possible Arima Models For Price

ARIMA Model			
(0,1,1)	(1,1,0)	(5,1,0)	(6,1,0)
(0,1,6)	(1,1,1)	(5,1,1)	(6,1,1)
	(1,1,6)	(5,1,6)	(6,1,6)

Model Diagnostics

After the parameters have been estimated, the adequacy of the model is tested using Ljung-Box statistics. This test uses all the sample of residual ACF of a fitted ARIMA model, not the original series on whether the ARIMA model has no autocorrelation. Table 4 shows the summary of the Q-statistics for each model.

Table 4: Summary of Q-Statistics for Arima Model

ARIMA Model	Summary of Q-statistics	Adequacy
0,1,1	$p < 0.05$	Not Adequate
0,1,6	$p < 0.05$	Not Adequate
1,1,0	$p < 0.05$	Not Adequate
1,1,1	$p < 0.05$	Not Adequate
1,1,6	$p > 0.05$	Adequate
5,1,0	$p < 0.05$	Not Adequate
5,1,1	$p < 0.05$	Not Adequate
5,1,6	$p < 0.05$	Not Adequate
6,1,0	$p > 0.05$	Adequate
6,1,1	$p < 0.05$	Not Adequate
6,1,6	$p < 0.05$	Not Adequate

From all 11 ARIMA models, only 2 models are adequate and can be used to model the data. The best model to be chosen is the one with the lowest AIC. ARIMA (1,1,6) has the lowest AIC value and will be used to model the value of price. Hence, the equation for ARIMA (1,1,6) is :

$$\begin{aligned} PRICE_t = {} & 12.55067 + 1.777543PRICE_{t-1} - 0.540967\varepsilon_{t-1} - 0.192355\varepsilon_{t-2} \\ & - 0.041517\varepsilon_{t-3} + 0.209250\varepsilon_{t-4} - 0.163923\varepsilon_{t-5} \\ & - 0.249549\varepsilon_{t-6} \end{aligned} \tag{5}$$

Data Modelling and Modelling Performances of ARDL and ARIMA Model

Table 5 summarizes the modelling performances of ARDL (2,2,0,0,2), ARDL (1,2,0,0,2) and ARIMA (1,1,6). By comparing the modelling performances from both ARDL and ARIMA models, ARDL (2,2,0,0,2) and ARDL (1,2,0,0,2) performs better in modelling the value of palm oil price. This is due to the fact that both MAE and MAPE for both ARDL model are smaller than ARIMA (1,1,6). This shows that ARDL outperforms ARIMA model in modelling the palm oil price.

Table 5: Modelling Performance of ARDL and Arima Models

Models	MAE	MAPE
ARDL (2,2,0,0,2)	100.0044	5.0520
ARDL (1,2,0,0,2)	100.3614	5.0675
ARIMA (1,1,6)	107.9314	5.5758

By comparing the modelling performances between the two ARDL models, ARDL (2,2,0,0,2) performs better than ARDL (1,2,0,0,2). This is due to the fact that both MAE and MAPE for ARDL (2,2,0,0,2) are smaller than ARDL (1,2,0,0,2). This shows that the model selected by using AIC outperforms model selected by using SBC. The ARDL models selected by AIC is relatively close to the best SBC model since the difference only occurs at the lag of logarithmic price (ln $PRICE$) variables.

CONCLUSION

In modeling the price of crude palm oil, the ARDL model constructed is better than ARIMA model. This is due to the ARDL model uses the past and the present of price and other variables related to price while ARIMA model only uses the past and the present of price. However, both models are suitable for modelling the price of palm oil since all of the models only deviate 5% from the actual value. By performing ARDL bound test, the long-run relationship between the price of palm oil with its determinants (monthly production, import volume, export volume and closing stock) can be estimated. From the long run equation, the production and export have positive impact on price while import and stock have negative impact on price of palm oil which is consistent on both models. This study implies that the government should reduce the import and closing stock of palm oil to upturn its price. For future recommendation, other factors that might affect the price of palm oil such as yield, and oil extraction rate should be integrated by other researcher.

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